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DEVELOPMENT OF A DECISION SUPPORT SYSTEM FOR THE DEPARTMENT OF ENERGY'S SELECTION OF WASTE SITE REMEDIATION TECHNOLOGIES

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The Department of Energy is faced with the complex decision of selecting technologies for waste site remediation. This research focused on developing a decision support system to aid the decision maker in selecting the best strategy of remediation technologies. Specifically, the research outlined the use of multiple attribute utility theory using exponential attribute utility functions with a simple additive objective function. A decision analysis model was developed which incorporates life-cycle cost data, risk information, and user input, to analyze the technology choices. The best available data was used to demonstrate the capabilities of the model. The model provides the decision maker with information on utility, cost, and time. Cumulative and frequency distributions illustrate the dominance of technology choices and the variance in the results. Cost and time plots allow the decision maker to see the trade-offs inherent in the utility functions. The model also allows for sensitivity analysis in the form of rainbow and tornado diagrams to display the affects of changes in the values of the input variables. Overall, the model provides a generic tool that can be used to make better decisions and can be easily manipulated to reflect changes in the remediation process.

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MARCH, 1996

Abstract

The Department of Energy is faced with the complex decision of selecting technologies for waste site remediation. This research focused on developing a decision support system to aid the decision maker in selecting the best strategy of remediation technologies. A decision analysis model was developed which incorporates life-cycle cost data, risk information, and user input, to analyze the technology choices. The research outlined the use of multiple attribute utility theory using exponential attribute utility functions with a simple additive objective function. The best available data was used to demonstrate the capabilities of the model. The model provides the decision maker with estimates of the cost and time distributions, and the associated utility. Cumulative and frequency distributions illustrate the dominance of technology choices and the variance in the results. Cost and time plots allow the decision maker to see the trade-offs inherent in the utility functions. The model also allows for sensitivity analysis in the form of rainbow and tornado diagrams to display the effects of changes in the values of the input variables. Overall, the model provides a generic technology selection tool that can be used to make better informed decisions and can be easily manipulated to reflect changes in the remediation process.

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I. Introduction

1.1 Background

The Department of Energy (DOE) is responsible for the remediation of an estimated 3.1 million cubic meters of hazardous and radioactive waste that is buried or stored at various locations across the U.S. [DOE/ID-10513, 1995: 4]. Unfortunately, most of this waste was disposed of when environmental regulations were less stringent. Because of this, sites may include mixtures of both hazardous and radioactive waste stored in forms ranging from steel 55-gallon drums to cardboard boxes.

The DOE reports that $200 to $300 billion will be spent between the years 1995 and 2070, to manage and remediate the waste sites [DOE/EM-0119, 1995: xiv]. Waste site remediation is a multi-step process. At each step, a decision must be made as to which technology should be selected for that process. The Landfill Stabilization Focus Area in EM-50 concentrates on developing and selecting technologies for five processes: Characterization, Stabilization, Retrieval, Treatment, and Containment. These processes, along with disposal and monitoring are illustrated in Figure 1.1 as outlined by the DOE [Mohiuddin, 1994] [DOE/ID-10513, 1995: 18-20]. Brief descriptions for each process are given as defined by the DOE [DOE/EM-0251, 1995: xiv-xvi].

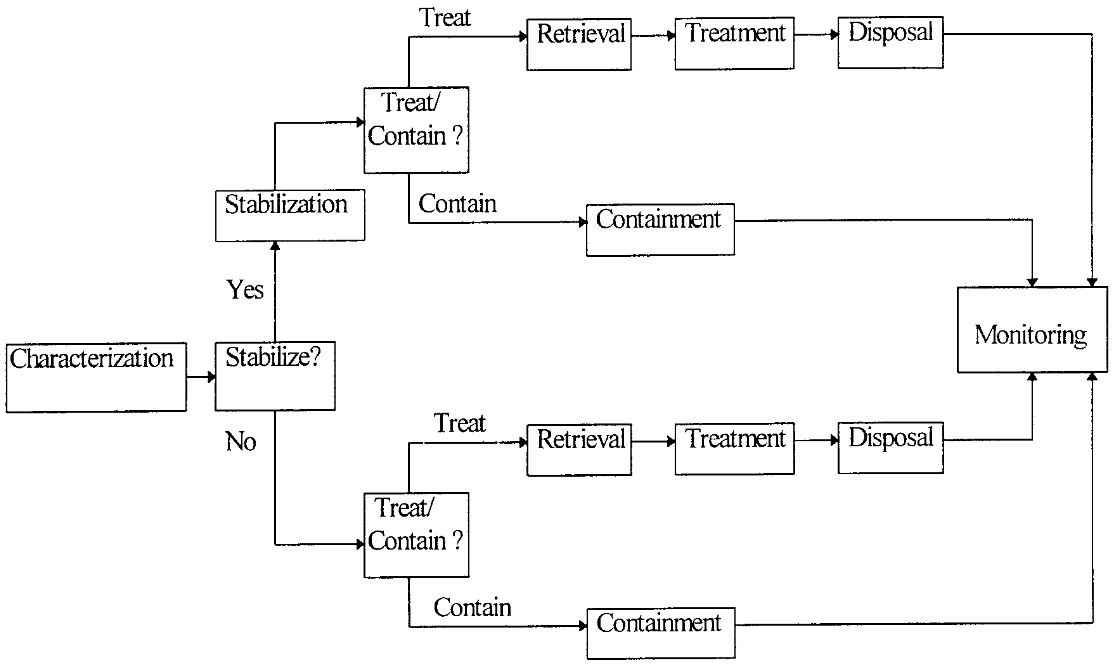


Figure 1.1 Remediation Decision Process

- *Characterization* is concerned with the identification, quantification, and location of waste within the site. In addition, characterization determines the size and type of items in the site.

- *Stabilization* involves the immobilization of contaminants in order to reduce their impact to the environment.

- *Retrieval* involves removing the waste and contaminated soil. Each method depends on the type and location of waste found during characterization.

- *Treatment* is the actual processing of the waste material. Again, waste types and desired residual waste form dictate the treatment options.

- *Disposal* is concerned with how the treated waste form will be handled. These options include on-site storage, storage at an off-site location, and other options. The available choices depend on the volume and hazard level of the treated waste.
- *Containment* confines the buried waste to a controllable area. This process prevents the migration of the waste, perhaps until an effective treatment is available, or until the waste becomes less volatile.
- *Monitoring* considers methods to verify that the treated or contained waste is maintained in a conforming environment.

For each process of remediation there exist several technology options which may be used. Additionally, new technologies are being developed and tested to improve each step in the process. Depending on the site location, technologies are chosen to characterize and assess the waste site. Once the characterization technology is determined, technologies are chosen to either treat or contain the waste. Technologies are then chosen to monitor the treated or contained waste form. The chosen technologies for each process make up the remediation strategy.

Presently, the DOE lacks a formal tool to support the decision maker when selecting remediation technologies. In a previous study, a life-cycle cost (LCC) model was developed to calculate the LCC for remediation technologies [White et al., 1995]. This model uses stochastic cost inputs and simulation to determine the LCC for technologies. Decision analysis techniques can use this information, combined with

information about technology risk and probabilistic process times, to help the decision maker select the best mix of remediation technologies.

1.2 Problem Statement

The DOE requires a decision analysis (DA) model, which incorporates LCC, total process times, and risk information, to be used for the selection of a broad spectrum of technologies for landfill stabilization and remediation. The model will be tested using technology data gathered and estimated by MSE Inc. in Butte, Montana. This data will then be used to analyze the remediation of the Idaho National Engineering Laboratory (INEL) test pit 9.

1.3 Research Objectives and Scope

This research has two primary objectives. The first is to develop a decision analysis model that uses data for cost, time, and risk, in order to compare technology strategies for landfill waste remediation. The second is to apply the DA model to the supplied technology data to demonstrate the analysis capabilities and techniques. The decision support system will take advantage of Multiple Criteria Decision Making (MCDM) techniques such as utility, dominance, expected value, and sensitivity analysis.

Particular emphasis will be placed on the modularization of the model as well as graphical output to aid the decision maker. A generic model will allow future analysis efforts to include new technologies for new waste sites with minimum adjustment to the model. Using output such as cost and time distributions, rainbow diagrams, and tornado

diagrams allows the decision maker to easily see optimal strategies and the relationships between the strategy objective function values and the input variable values.

1.4 Approach

The DA model requires input from the LCC model and a risk analysis module, as well as input concerning user preferences. The technology data is provided by MSE, and site data from the INEL test pit 9 is used as the hazardous waste to be remediated.

The DA model will use the cost, time, and risk data to determine the total cost and remediation time distributions for specific technology strategies. To assist the decision maker, the attributes of cost and time can then be combined using utility theory. The utility functions will reflect the decision maker's risk attitude within the ranges of the two attributes. The different remediation strategies can then be compared using cost, time, and utility to the decision maker. Finally, sensitivity analysis will be performed and recommendations can be made as to the input variables and data. The ability to perform sensitivity analysis is critical to the DOE. The model will allow for sensitivity analysis of technology parameters, model variable values, and utility criteria, which can be varied to show how sensitive the resulting decision policy is to changes in the input.

1.5 Overview

In chapter 2, the current techniques for MCDM and utility theory are reviewed. Also, similar decision support analysis efforts are discussed, along with other decision analysis methods. Chapter 3 discusses methodology for developing the DA model. The

utility functions, objective functions, and distributions are developed using the methods reviewed in Chapter 2. Chapter 4 discusses the analysis of the test data and the usefulness of the model using different analysis scenarios. In Chapter 5 conclusions are drawn and recommendations for follow-on work are presented. Detailed appendices are included to fully explain the elements of the DA model, the test technology database, and the analysis results.

II. Literature Review

2.1 Introduction

In this literature review, the use of Multi-Criteria Decision Making (MCDM) techniques to model and analyze the DOE's remediation process will be documented along with the criteria and information used in the modeling and analysis effort. This is accomplished by reviewing the current procedures for similar decision analysis problems, discussing the different methods available, and assessing the objectives and metrics used in previous studies.

2.2 Decision Analysis

Choosing technologies for waste site remediation is a very complex decision. Clemen asserts that decisions are difficult when they deal with several issues, involve uncertainty, have multiple objectives, and are sensitive to their inputs [Clemen, 1991: 2]. Selecting remediation technologies involves all of these characteristics. Waste site remediation involves many complicated processes. Compounding the complexity is the fact that cost and time for each technology is unknown, cost and time are conflicting objectives, and changes in certain input variables like the interest rate can greatly affect the optimal decision policy. Decision analysis provides the decision maker (DM) with more useful information. When the DM is better informed, better decisions are made [Clemen, 1991: 4].

Although there are numerous decision analysis tools and techniques, the decision analysis process generally remains the same. First, a model of the decision situation is developed. Options are then evaluated using the model. Finally, analysis is performed to ensure the validity of the results [Howard, 1988: 680].

A great deal of research has utilized decision analysis tools for technology selection. Most studies employ the same basic technique, with only slight variations for the particular problem. Buede et al. analyzed the U.S. Marine Corps' (USMC) acquisition of the mobile protected weapons system, a decision similar to the DOE remediation technology decision. They use the method of MCDM to determine the best weapons system based on the needs of the USMC. This decision involves several conflicting objectives including mobility, survivability, and transportability. Experts in the field provided an excellent source for determining the criteria to evaluate technologies. Once the objectives and the criteria were clear, Buede et al. determined weights which model the importance of each criteria [Buede et al., 1992: 112-113]. The weights represent the decision maker's view of the trade-off between the criteria. The criteria, or values, "provide the foundation for interest in any decision problem" [Keeney, 1992: 55].

Technology evaluation is also performed extensively in the field of manufacturing. Competitive manufacturing firms must upgrade or change their equipment in order to improve their capabilities. Despite the differences in the apparent decision situation, the selection of manufacturing technologies can be a process very

similar to the selection of military weapons systems. In 1993, Fine analyzed the selection of flexible manufacturing technology for manufacturing firms [Fine, 1993: 711-750]. In his study, Fine followed the same general process of Buede et al. The fundamental criteria such as capacity, flexibility, installation time, and upgradability for selecting a manufacturing technology are somewhat different than the criteria such as survivability, mobility, and firepower used to select a weapons system, but the decision analysis process is comparable [Fine, 1993: 724][Buede et al., 1992: 113]. Similarly, the objectives and criteria for selecting technologies to remediate waste sites may be different than those for other decisions. Although the criteria and trade-offs are specific to each study, the use of decision analysis and multiattribute techniques is a viable method for studying the selection of technologies.

2.3 Multiattribute Analysis

Multiattribute evaluation permits many issues to be evaluated simultaneously making it a useful tool for technology evaluation [Fine, 1993: 724]. Again, there is a basic process that most studies follow, but each makes slight changes in particular calculations [Corner and Buchanan, 1995: 109].

1. Develop objectives and criteria to meet the objectives
2. Determine the form of the objective and utility functions
3. Determine the importance of each attribute (weight)
4. Evaluate alternative and perform sensitivity analysis

One common discrepancy among researchers, is the method by which the weights for the criteria are calculated [Corner et al., 1995: 110]. Buede et al. uses weights that are determined simply by working with the decision maker and allowing experts to make suggestions as to the importance of each criteria [Buede et al., 1992: 114]. Although many methods use the decision maker's inputs directly, some methods involve mathematical calculation of the criteria weights.

2.3.1 Additive Utility Functions. In most cases, the use of criteria weights implies an additive type of utility function. An additive utility function has the general form shown in equation (2.1).

$$U(x_1, x_2, \ldots x_n) = k_1 U(x_1) + k_2 U(x_2) + \ldots + k_i U(x_i) \tag{2.1}$$

where $U(x_1,x_2,\ldots x_n)$ = total utility, $U(x_i)$ = utility for attribute i,

k_i = weight for attribute i, x_i = level of attribute I

The lack of an interaction term in the previous function implies that there are no interactions between the criteria. Keeney and Raiffa explain this and other independence requirements for using an additive utility function. Keeney and Raiffa define the necessary and sufficient conditions for additive utility functions as additive independence. They assert that two attributes are additive independent if lotteries in one attribute can be compared independent of the other attribute. In graphical terms, attributes A and B are additive independent if the DM is indifferent between the two

lotteries X and Y, shown in Figure 2.1. If additive independence holds for the criteria, then the additive utility function can be applied [Keeney and Raiffa, 1976: 229-230].

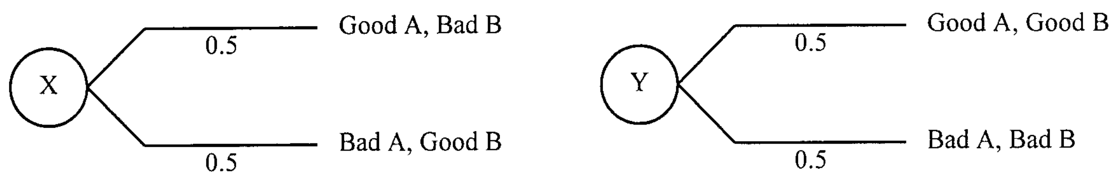


Figure 2.1 Additive Independence Lotteries

The additive utility function is only one form of utility function. There are other more complicated forms for criteria that do not meet independence requirements and that exhibit other functional forms. In his 1995 study, Stewart shows that the additive utility function is usually appropriate and provides results similar to those found in more complicated utility functions. His results show that "there is very little to be lost in basing analysis for MCDM under uncertainty on a simple additive utility function" [Stewart, 1995: 255]. A simple utility function can be more intuitive to the user and can help to simplify the analysis of the model. Added to this, an additive utility function requires criteria weights that are generally simple to obtain and small in number [Stewart, 1995: 251-256]. Based on discussion and interaction with the principals for this study, it

appears that DOE decision makers are likely to relate to a simple additive function rather than a more complex utility function.

2.3.2 Criteria Weights. Regardless of the complexity of the objective function, weights must be determined to represent the importance of each attribute to the decision maker. Clemen explains three methods for calculating the weight for each objective criteria. The first method is called pricing out the attributes. Pricing out requires that the decision maker assess the nonmonetary attributes in terms of a cost attribute. Clemen's example involves the purchase of an automobile, where the criteria for evaluating the alternatives are price and life-span. In order to determine the weights for each criteria, the decision maker must assign a dollar amount to an increase in life-span. For example, the purchaser might be willing to pay $600 for an extra year of life-span. By transforming the attributes into common units, this price can then be used to determine the appropriate weights for each criteria [Clemen, 1991: 441]. Although pricing out criteria is a valid method for determining weights, it can become difficult for the decision maker to assign dollar amounts with all criteria. Added to this, dollars may not be applicable to some criteria which require other methods for determining criteria weights [Clemen, 1991: 448].

The next method described by Clemen for determining the trade-off between criteria is swing weighting. As with the other methods, the decision maker's judgment is used to help calculate swing weights. The first step involves determining the worst possible alternative. This 'virtual' alternative would score the lowest on all criteria.

Using the automobile example, the worst possible alternative would have the highest price and the lowest life-span. Next, the decision maker must decide which criteria, if increased to its best level, would yield the most increase in satisfaction, or utility. For example, the lowest price might be preferred to longest life-span. If price is decreased to the best level while life-span remains at its worst level, the decision maker gets some increase in utility. Once this is noted, we return to the worst possible case and increase the next criteria. Now price is high [redacted] is increased to equal the longest actual life-span. This setting results in some smaller increase in utility. Assuming the relationship is linear, the increase in utility is smaller because it was previously determined that a decrease in price was better than an increase in life-span. The weights are determined by comparing the increase in utility from swinging each criteria from its worst to best level. For example, having the longest life-span may have resulted in 75% of the improvement gained by decreasing price from worst to best. Using this, the weights for the two criteria can be calculated using the form in (2.2).

$$k_l = 0.75k_p \qquad 3/4k_p + k_p = 1 \tag{2.2}$$

$$k_l + k_p = 1 \qquad k_p = 4/7,\ k_l = 3/7$$

where k_l : weight for life span, k_p : weight for price

For convenience, the weights are forced to sum to one. This decreases the dimensionality of the problem because both weights do not have to be determined. Added to this, it ensures that the weights are relative to each other. One advantage to

using swing weights is that they are sensitive to the value range of the criteria. For example, if the difference between the longest life-span and the shortest life span is 1 year, then the decision maker would likely assess a small increase in utility from swinging life-span from its worst to best level. This would result in a small weight for life-span. Swing weights also allow for the best possible alternative to be considered if the decision maker cannot assess the worst possible case. In such a case, instead of an increase in utility, the decrease in utility is evaluated for each criteria [Clemen, 1991: 448-450].

The last method that Clemen describes is the lottery assessment of weights. This method requires that a lottery be set up like the one shown in Figure 2.2. The figure shows two options where one is certain and the other involves uncertainty. In order to determine the weight for each criteria, the decision maker must assess the value of p for which he is indifferent between alternative A and alternative B. This value is used as the weight for the one attribute at its best level for alternative B. This process must be repeated for the remaining criteria. The final criteria weight will not require a lottery assessment if we assume that the weights sum to one. One important advantage to using the lottery technique is that it enables the decision maker to include his or her risk attitude in the assessment of the alternatives [Clemen, 1991: 451-452].

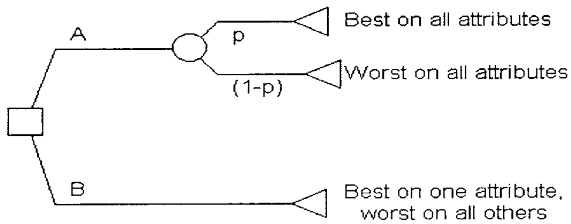


Figure 2.2 Lottery Technique for Assessing Weights

Another method of assigning weights to criteria, is called the analytical hierarchy process (AHP). Despite some shortcomings, AHP is one of the most popular methods applied to determine multiattribute weights [Ra, 1991: 595]. This method involves pairwise comparisons. The development below follows that of Winston; however, the method was originally developed by Thomas Saaty [Winston, 1994:798-804]. To accomplish the pairwise comparisons, the decision maker creates a matrix consisting of values representing his preference between two criteria. These matrix elements are denoted a_{ij} and are generally based on a standard similar to the one shown on the following page. The actual scale and descriptions can be changed but a standard is necessary to evaluate the criteria consistently.

a_{ij} = 1 : criteria i and j are equally important

3 : criteria i is weakly more important than j

5 : criteria i is strongly more important than j

7 : criteria i is demonstrably more important than j

9 : criteria i is absolutely more important than j

2, 4, 6, 8 : intermediate values

For n number of criteria, the matrix is made up of n rows and n columns. Once the matrix is formulated, the weights for the criteria can be calculated. This is usually accomplished using eigenvector calculations. Complete calculations are shown in Appendix A. Weights can also be approximated by normalizing the columns of the matrix A, then taking the average value in each row. These averages provide approximations to the criteria weights [Winston, 1994: 801]. Once the criteria weights are calculated, they should be checked for consistency.

It is important that the decision maker make consistent assessments of the criteria in order for the AHP to produce confident results. On the other hand, slight inconsistencies are usually acceptable and are common in models that have a large number of criteria. Usually, a consistency index is calculated to determine how consistent the decision maker was in evaluating the criteria. Complete calculations of this index are shown in Appendix B. If this consistency index is small, then the amount of inconsistency is acceptable [Winston, 1994: 798-802].

To deal with some criticism of the initially proposed approach, variations of the AHP have been developed. Ra describes a similar method that he calls the hierarchical decision process (HDP). This method changes the scale by which criteria are compared, the calculations for criteria weights, and the measure for inconsistency. Ra uses a ratio

scale from the decision maker's scoring on a 100 point scale. If criteria A scores 60 and criteria B scores 40, then the ratio is 60/40 = 1.5. This scaling allows the decision maker more flexibility in his or her assessments. In order to compute weights, Ra recommends a logarithmic least squares method. The complete algorithm is shown in Appendix C. Ra uses this method because it is suitable for ratio scoring, obtains identical results to the eigenvector calculations once the ratios are determined, and allows for sensitivity analysis [Ra, 1991 : 595-599]. The AHP and HDP do share some of the same drawbacks in that they are sensitive to the changes in the alternatives and criteria. If an alternative is added or taken away then the complete AHP analysis has to be repeated. This is a major drawback for a generic decision support system.

2.3.3 Criteria Scoring. Clemen also explains the different methods for determining the scores for particular criteria. One method is called proportional scores. It may be possible to use the actual values for cost and life-span, but scaling these values can ease the calculation of the criteria weights and simplify the explanation of the problem. In the automobile example, if we know the best and worst prices, we can scale these values to a range of 0 to 1, where 1 is the best price and 0 is the worst price. If we assume proportional scores, then the slope of the line between the best and worst case allows for any alternative that falls in this range to be scored. Figure 2.3 shows an example for price.

Figure 2.3 implies that the worst price has a utility of 0 while the best price has a utility of 1. Now any alternative price that falls between these values can easily be scaled

to a utility value. The major drawback of using proportional scoring is that it assumes risk neutrality. In some instances, the utility curve for price may not be a straight line. This leads to the utility function method of scoring criteria.

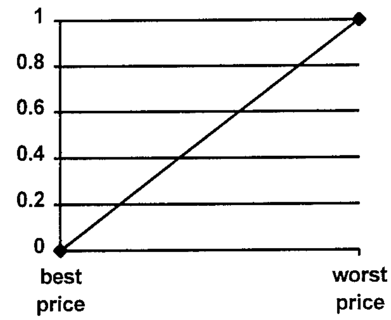


Figure 2.3 Proportional Score for Price

Unlike the above situation, the DOE selection of remediation technologies involves a great deal of uncertainty concerning the actual cost and time for each technology. Clemen recommends the utility function method of scoring criteria when the decision involves uncertainty and trade-offs [Clemen, 1991: 474]. This method requires that the model assess the decision maker's risk attitude so that an appropriate function can be used to score the criteria. There are several methods for doing this. One option is to have the decision maker evaluate a certain value that is equivalent to a given gamble with probabilities for different criteria situations. A similar method involves evaluating probabilities for a given certainty equivalent. Another approach requires that a mathematical function be used. The exponential utility function is widely used to

incorporate risk into the scoring of alternatives for criteria [Clemen, 1991: 382]. The equation for the exponential utility function is shown in (2.3).

$$U(x) = 1 - e^{-x/R} \tag{2.3}$$

where R is the risk tolerance measure

Larger values of R imply that the decision maker is willing to accept more risk. The risk tolerance level must be determined in order to use the exponential utility function. Different methods can be used to determine the risk tolerance for a decision maker. Lottery assessments can be used, as well as general guidelines that relate risk tolerance to measures like net income, sales, and equity [Howard, 1988: 689-670].

Clemen demonstrates that the exponential utility function exhibits constant risk aversion, which means that the decision maker's attitude toward risk never changes regardless of his or her level of wealth. Because of this constant risk aversion, the exponential utility function is usually more applicable to large companies than individuals. If this assumption holds, the exponential utility function can be applied [Clemen 1991: 382].

The scoring methods above can be applied when the criteria involve actual numeric values. However, another method may be preferred when the criteria is more qualitative. The ratio method of scoring requires the decision maker to compare outcomes and determine scores for each outcome. These scores are then scaled to a range of 0 to 1. The ratio scoring technique allows for any type of criteria to be scored which

enables cardinal or ordinal data to be used [Clemen, 1991: 439-447]. Equation (2.4) shows the general form for ratio scoring.

$$\text{Score}(x) = a + b\cdot(x), \text{ where a and b are found by solving:} \tag{2.4}$$

$$0 = a + b\cdot(\text{worst score})$$

$$1 = a + b\cdot(\text{best score})$$

Once a and b are calculated, any alternative score can be calculated. These scores all range from 0 to 1. Ratio scoring allows both cardinal and ordinal data to be scored. Ordinal data values can be used while cardinal data can be given subjective values. For example, if a blue car is worth twice as much as a yellow car, then Blue = 100 and Yellow = 50. Because of this, ratio scoring provides a method to evaluate any type of alternative [Clemen, 1991: 447].

Finally, the AHP can be used for scoring alternatives on criteria. The process is almost identical to the weighting procedure. It requires the decision maker's assessments and uses this to create a matrix. This matrix is then used in eigenvalue calculations to determine the normalized score given to each alternative. Once this is done, the results can be checked for consistency [Winston, 1994: 802-804].

2.4 Sequential Decisions

In their 1993 article, Cook et al. address the problems of sequential decisions containing ordinal and cardinal criteria. Concurrently, they present a new method for

calculating the weights for criteria in a multiattribute decision. In their study, Cook et al. use an example of a mining company that is trying to choose a production design and a supplier for that design [Cook, Johnston, and Kress, 1993: 130]. This example involves sequential decisions for production and supplier, which is similar to the DOE technology selection decisions for each sequential process. A decision tree representation of the example is shown in Figure 2.4, and shows that the supplier decision is influenced by the previous decision.

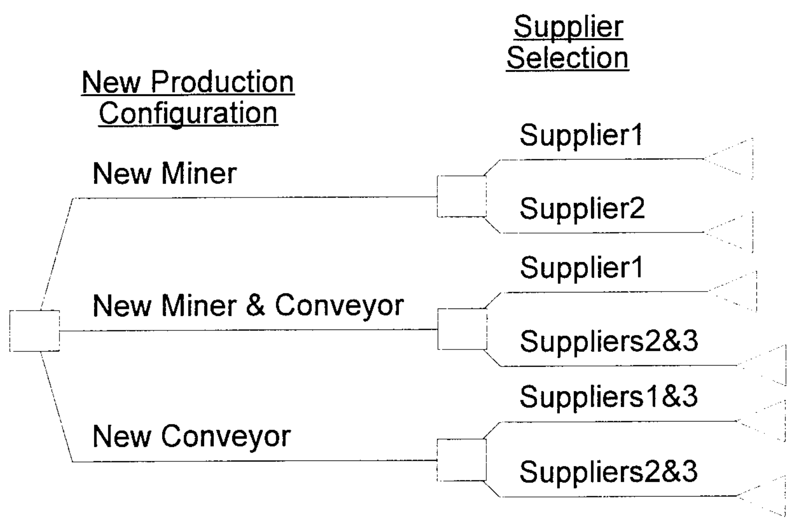


Figure 2.4 Decision Tree for Sequential Decision Example

2.4.1 Sequential Model. In order to frame their decision process, Cook et al. use a decision tree structure. The exact structure used is very similar to the one shown in Figure 2.4. When a decision involves several stages that produce their own outcomes, a decision tree can provide a useful means of viewing the problem [Cook et al., 1993: 133]. The structure of their decision tree incorporates the general structure used in decision

analysis with decision nodes, event nodes (chance nodes), and outcome nodes. Cook et al. make two assumptions for their decision tree structure, which may apply to the DOE decision process. Specifically, each level of decision has its own set of criteria,and all of the decisions are made before events occur [Cook et al., 1993: 135].

2.4.2 Model Calculations for Cook et al. The first decision is to determine the production system design. This decision is based on three qualitative criteria. The second decision is to choose a supplier, which is based on both qualitative and quantitative criteria. It is important to note that they assume that the criteria are known in advance. In order to choose alternatives based on the criteria, Cook et al. use a ranking method similar to an AHP approach. The method ranks alternatives based on each criteria. For objective data, actual values are used where more is assumed to be better. For cardinal data, the alternatives must be given ranks for each criteria, and the decision maker must assess the importance of being ranked at a given position for each criteria. The criteria are then ranked in order of importance to the decision maker. Once this scoring is complete, a linear programming optimization model is used to determine the weights given to each criteria [Cook et al., 1993: 129-133].

The model that is used to calculate the weights is similar to a data envelopment approach [Cook et al., 1993: 136]. The objective function in the model has a goal of maximizing the total worth of each alternative subject to some implied constraints on these values [Cook et al., 1993: 136]. The importance of this model is that it allows for the rank of alternatives and criteria to be considered [Cook et al., 1991: 193]. In order to

solve the multi-level decision tree, weights must be calculated for the criteria involved in each decision. Cook et al. work backwards in the case of sequential decisions and use the optimization model to determine the weights at each step. This type of model is very complex to implement and difficult for the decision maker to assess. However, this model is flexible in that it allows for ordinal and cardinal data without a utility assessment, and it can be applied to dependent decisions [Cook et al., 1993: 141-144].

2.5 DOE Objectives and Criteria

In order to assure that the decision model for the DOE is valid, the appropriate criteria must be determined. As previously discussed, determining the criteria for making decisions which represent the true values of the decision maker is a fundamental step in the decision analysis process.

2.5.1 Objective Criteria. In decisions that involve the selection of technologies, cost is usually included as a primary criteria. In order to determine the other appropriate criteria, it is important to elicit the decision maker's values. The challenges given to the DOE in remediating waste sites were to remediate: 1) faster, 2) better, 3) cheaper, and 4) safer [Mohiuddin, 1995]. Thus, the DOE's goals for this study are primarily concerned with risk prediction for cost, time, and safety; cost savings; and developing better technologies [Mohiuddin, 1995]. This plan, along with the DOE's agreements to meet milestones, make cost and time reasonable objective criteria to select waste remediation technologies [DOE/ID-10513, 1995: 6]. Other objectives like safer and better remediation require more subjective criteria.

2.5.2 Subjective Criteria. Although cost and time are important to the DOE, other measures such as safety and technology transferability are influential in choosing a remediation technology. In 1995, a study was done for the Westinghouse Savannah River Company. This study developed criteria for the selection of new treatment technologies and for the prioritization of waste streams. The Savannah River Site study treatment technology criteria are given below.

1) System implementability
2) System maintainability
3) Secondary waste generation
4) Health and process hazards
5) Final waste form
6) Cost

Although the above criteria were developed for treatment technologies, they can all be applied to each remediation process. All of the criteria were scored subjectively, with the exception of cost [WSRC-RP-95-0576, 1995: 1-7].

2.6 Summary

The literature indicates that multiple criteria decision making techniques are appropriate for evaluating problems similar to the DOE's selection of technologies for waste site remediation. The selection of technologies for waste site remediation involves many influencing factors such as money, safety, and government regulations. Added to

this there are risks of failure and of exceeding budget and time constraints. Using conflicting attributes such as cost and time also warrants the use of decision analysis and multiattribute techniques. Finally, this problem involves many variables, examples of which would be interest rates, and process overlaps that greatly affect the results of the study. To utilize multiattribute analysis, utility functions for each criteria must be determined. The exponential utility function has been shown to be applicable to similar situations particularly with large companies and government agencies where constant risk aversion can be used. Determining the exact form of this function can be accomplished through the lotteries and other discussed techniques. There are also computer programs that can aid in developing these functions. Provided that the appropriate conditions are met, the additive utility function has proven to be an accurate and simple form to be used for the overall utility function. Assessing the weights for this function can be done using lotteries or other methods, and there are also computer programs available to calculate these values. Time and cost have been shown to be viable objective criteria for selecting technologies. More subjective criteria can also be used to choose technologies for remediation.

III. Methodology

3.1 Introduction

Based on an examination of the literature and the DOE problem, multiattribute utility analysis was selected as the best method for modeling the selection of waste site remediation technologies. Utility theory provides a mathematical function to capture the decision maker's revealed preferences toward each attribute and the risk involved. Utility functions not only provide a straightforward way to score alternatives, but they also incorporate the decision maker's attitude toward risk. Due to the uncertainty and trade-offs involved in selecting technologies, utility functions provide the best method for modeling the decisions [Clemen, 1991: 445]. In particular, the constant risk aversion exhibited by most companies and governments lends naturally to the exponential utility function.

Research also suggests that an additive value function is an appropriate objective function for most cases of multi-attribute utility analysis. It is relatively simple to formulate and analyze. For studies that involve uncertainty, like the DOE's selection of remediation technologies, Stewart concluded that the additive value function can perform as well, or better than other more complicated value functions [Stewart, 1995: 255-256].

3.2 Decision Analysis Model

A model for the DOE decision process for selecting remediation technologies was developed based on the findings of the literature review, field visits, and discussions with

key stakeholders. The complete formulations are explained in the following sections. Figure 3.1 diagrams the flow of information between the different modules that make up the decision support system. The model incorporates all of the assumptions and capabilities outlined by the DOE. It uses cost, time, and risk input for each individual technology. This input data is from the life-cycle cost module and the technological risk characterization framework, and is stored in a spreadsheet. The DA model uses this information to model the uncertain time and cost of individual technologies which are then combined to allow computation of total cost and time for feasible strategies of technologies. Using these attributes, the decision maker can apply the model to determine the best strategy on the basis of cost, time, or a combined utility of both attributes.

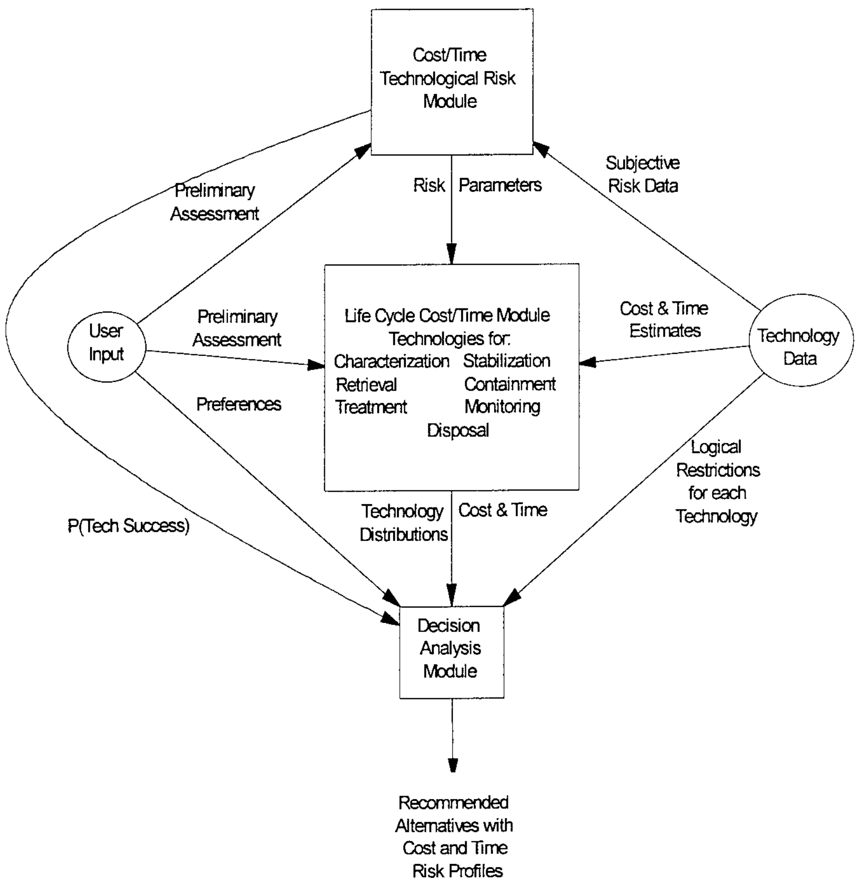


Figure 3.1 Decision Support System

Basically, the model follows the sequential remediation decisions and determines the total time required for each feasible strategy of technologies. Using this information, the present value of the total cost for the strategy can be calculated. The model calculates when a technology is to be utilized and when it is available for use. The DA model can therefore calculate the cost of using it at that point in time. Constraints for total cost and time are used to eliminate strategies that exceed budget and schedule limitations, while compatibility constraints ensure that the technologies can be used together. A value function that relates the decision maker's preference and utility for time and cost enables

the model to choose strategies based on the combination of both attributes. The following sections completely detail the development of the decision analysis model. The code for the complete DA model is in Appendix D.

3.2.1 Model Development. In developing the model, the decision process and relationships had to be determined. The basic decision process was provided by the DOE. This structure is shown in Figure 3.2. Each block represents a decision. All but two of these decisions involve the selection of a technology to perform the specified process represented by the block. Only the Stabilize and the Treat/Contain blocks are yes/no decisions that determine how the waste site is remediated.

Figure 3.2 shows the seven different processes that can be involved in remediating a waste site. Explanations for each process were given previously in Chapter 1. Each process involves a technology that implies a cost and time. The individual processes combine sequentially to make up the entire remediation process. The model is structured in this same fashion. Each process involves the calculation of cost and time for a particular technology, which are then combined together to calculate the total expected cost and time for a strategy of technologies.

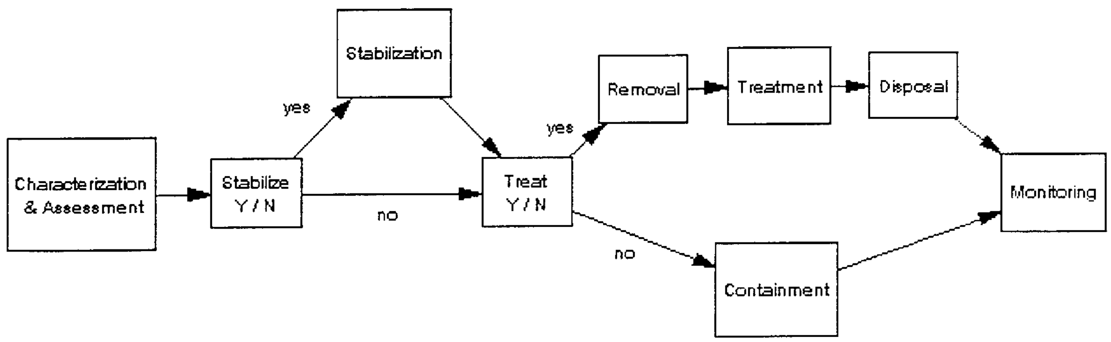


Figure 3.2 Waste Site Remediation Decision Process

The decision structure in Figure 3.2 can easily be translated into a decision tree. The decision tree in Figure 3.3 is the complete structure used by the DA model. The technology decision nodes are followed by the uncertainty nodes for technology failure, cost, and time, within each process. Each technology in the given decision path has a cost and time element represented by an uncertainty node. Figure 3.4 is the structure for the decision nodes shown in Figure 3.3. This structure is identical to the DOE decision process. In this illustration, there are three technology choices for each process. Each path through the tree represents a different technology strategy for remediating a given waste site. This situation was adopted for the present study.

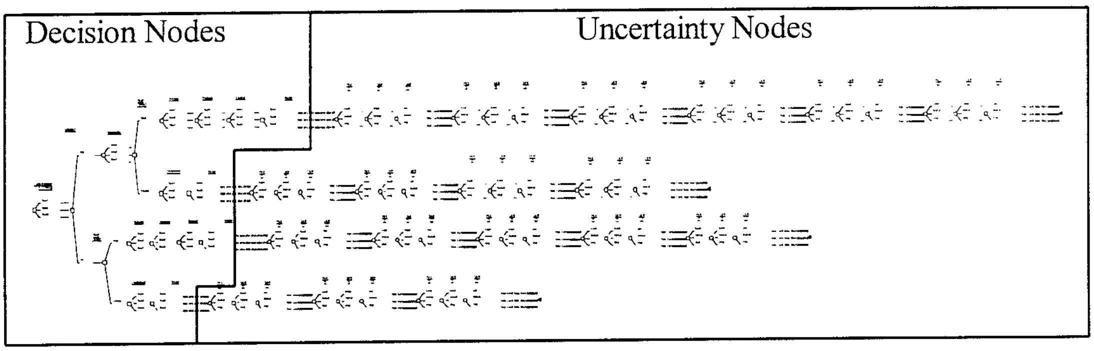


Figure 3.3 Complete Decision Tree

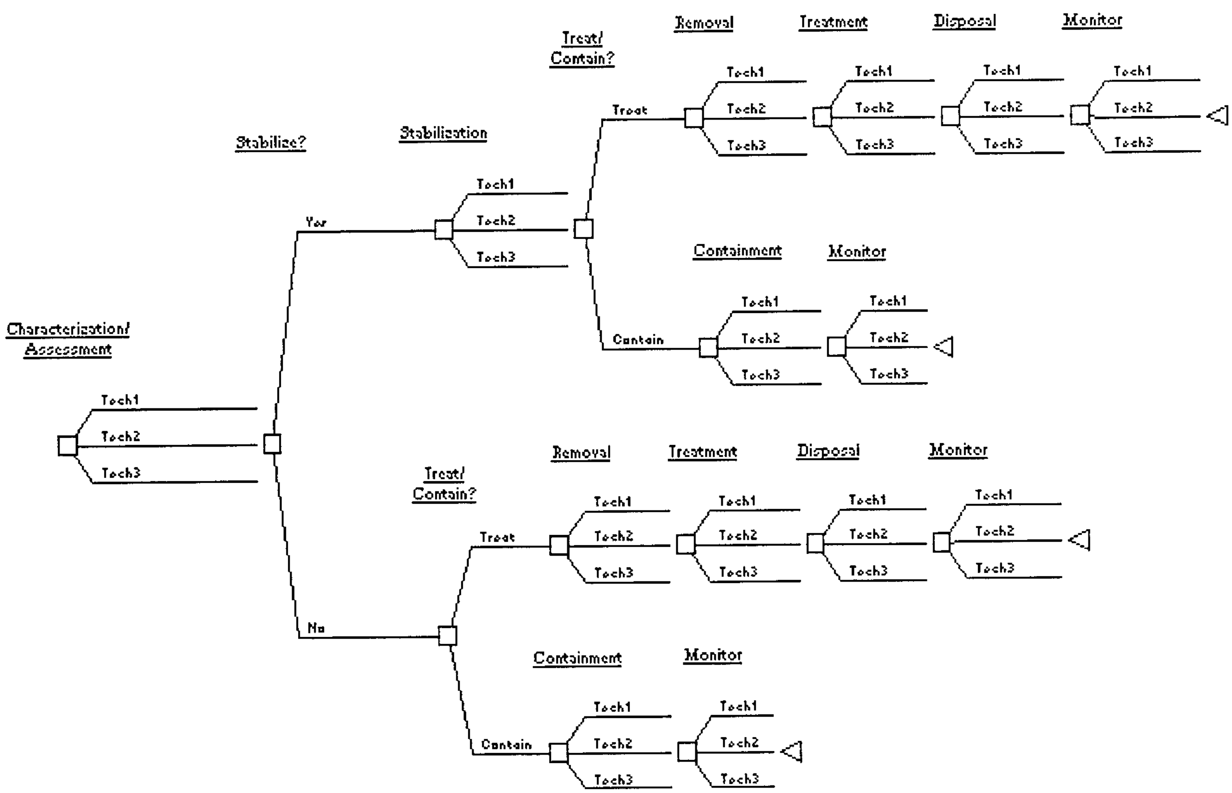


Figure 3.4 Decision Nodes for Selecting Technologies

In order to calculate the costs and times, the decision process has to be expanded so that each element and relationship can be modeled. The influence diagram provides a graphical representation of the relationships between the key elements of the decision process. Figure 3.5 shows the complete influence diagram for the DA model. The diagram is divided into the processes involved in remediation. Each process is modeled almost identically to the others. The process models calculate the cost and process time associated with using a chosen technology for the particular process. The influence diagram shows the elements and relationships in each decision, while the decision tree shows the timing and structure of the entire process.

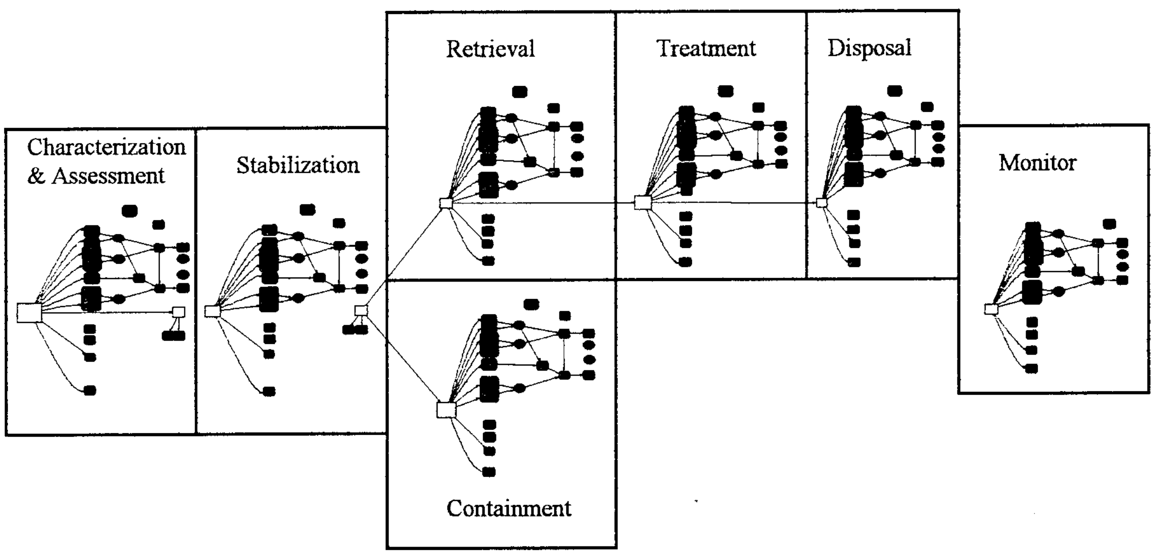


Figure 3.5 Influence Diagram for DA Model

3.2.1.1 Individual Process Models. Each process model uses similar structure and calculations. The result of each individual model is to calculate the cost of using the chosen technology for that process and to determine the time for the next process to begin. An influence diagram for a single process model is shown in Figure 3.6. Again, this model structure is identical to the ones for the other processes.

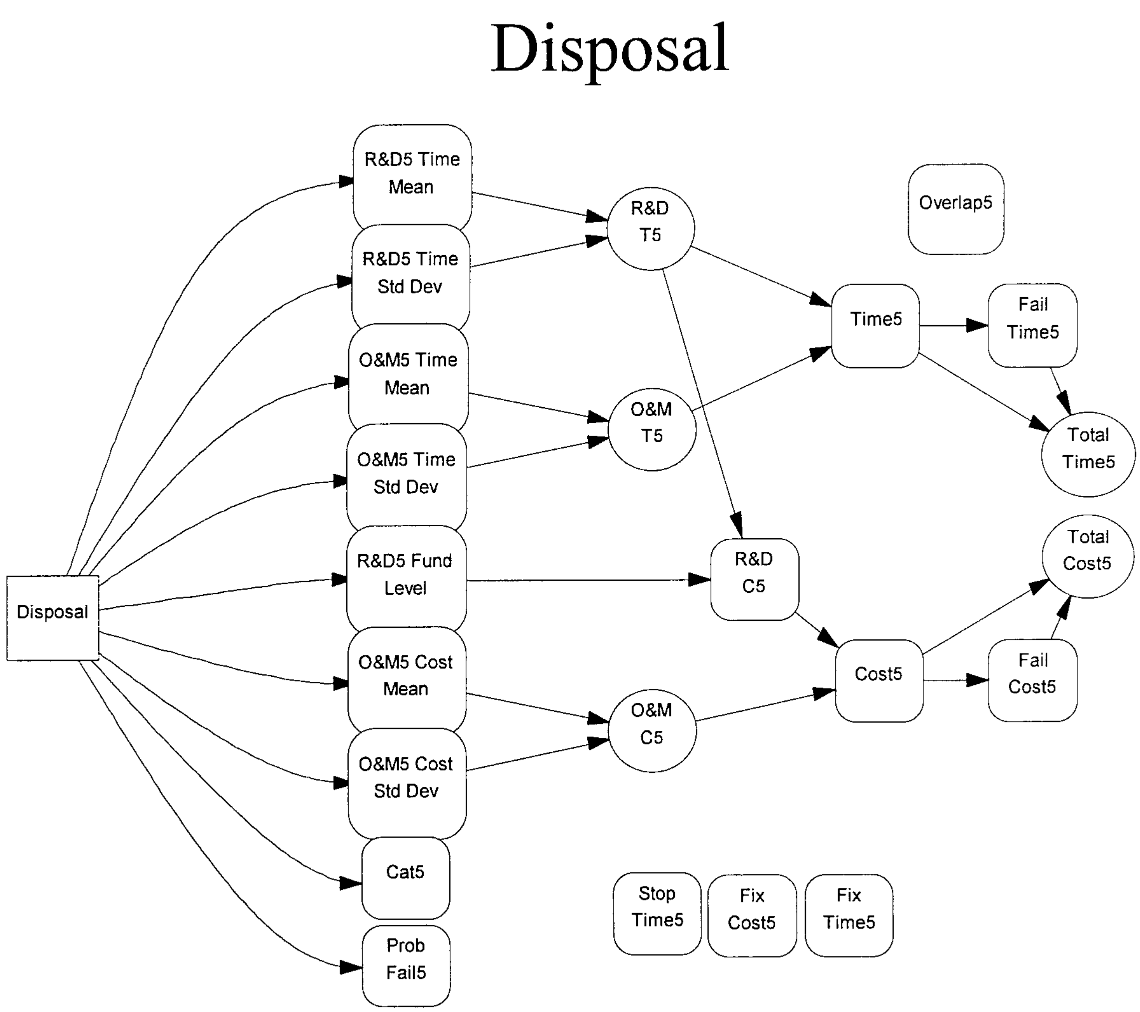


Figure 3.6 Individual Process Influence Diagram

Figure 3.6 shows an influence diagram representation for Disposal. In the influence diagram, the rectangular node represents the technology decision. Uncertain events are displayed as circles, and deterministic variable values are shown as round-cornered rectangles. When the disposal technology is selected, the R&D and O&M costs are determined, as well as the time required for R&D and O&M. If the technology is developed then it can be selected for immediate use. Otherwise the process is delayed until the technology is released from R&D and field testing. The time for O&M determines when the next process can begin. However, the remediation processes can overlap for some processes. It is realistic for a process to begin before the preceding process ends. For example, disposal is overlapped by monitoring because monitoring begins before disposal is complete. In this case, the time overlap is 100%, meaning that monitoring is required as soon as disposal begins.

The value nodes that follow the technology selection decision reference data from the spreadsheet containing the LCC and risk data. The cost and time values are used as parameters for the probability distributions which model the uncertain events for cost and time. The distribution output is then used to calculate cost and time. When a technology is selected, there is a possibility that the technology will fail. If this occurs, then additional cost and time will be required to complete the process. The DA model calculates the cost and time if the technology is successful, and the cost and time if the technology fails. When a failure occurs, a portion of the cost and time required for the failed technology is charged plus an additional penalty cost and time to complete the

process. The probability of technology failure, which is supplied by the Risk assessment framework, is then used in the uncertain events for total cost and time. The complete explanation and calculations for each variable are shown in Appendix E.

3.2.1.2 Complete Decision Model. The complete model of the decision process is built by combining the seven different process models. The basic decisions follow the same structure that was previously shown in Figure 3.4. The model calculates the expected value for cost and time. Therefore, technology decisions are made first, then the resulting cost and time for each strategy can be calculated. This is done by placing the decisions at the beginning of the decision tree followed by the resulting chance events used for the calculations of the technology strategy.

The DA model keeps track of the attributes for cost and time, as well as for the category of each technology in the strategy. The categories are used to ensure that the technologies in the strategy are compatible. If the technologies in the strategy are not compatible the strategy is excluded, otherwise the model continues. This compatibility constraint allows for technology relationships to be modeled. A specific treatment technology may require a specific disposal technology. By categorizing these technologies, the model only analyzes strategies that utilize compatible technologies. A complete explanation of the Boolean logic-based compatibility constraint is given in Appendix F.

The total cost and time values are also used to constrain the model. Budgets and schedules limit the amount of money and time allocated to remediate a waste site. A

constraint can be used to penalize strategies that exceed these limit values by assigning the strategy a penalized objective function value, such as an extremely high cost, time, or utility value. If the user wishes to exclude these strategies then the penalty can be increased to an extreme value. However, because the output is simulated, a strategy may exceed the limits on one trial while averaging below the limits. In this case, the more trials over the limits, the more penalized a strategy would be. The simulation method used for the DA model is called distributed sampling. This approach is explained in Appendix G.

3.2.2 Utility Functions. The DA model analyzes each possible combination of technologies and calculates the present value for cost and time for each strategy. Although the model can compare technologies based on cost or time, utility functions enable the decision maker's revealed preferences to be used as the basis for recommending technologies. Utility functions developed for each attribute can be combined in an objective function so that the trade-off between cost and time can be considered. These functions transform a value for cost or time into utiles, which is the utility to the decision maker. Utiles range from 0 to 1, where 1 is the highest utility and 0 is the lowest. For this model, the utility functions will change depending on the decision maker and the considered site.

3.2.2.1 Attribute Utility Functions. In order to develop an objective function, utility functions for the cost and time attributes must be determined. These attribute utility functions transform an expected cost or time for a strategy of technologies

into utiles, numbers that represents the worth of that cost or time to the decision maker. As Clemen suggests, the exponential utility function provides a robust and relatively simple functional form [Clemen, 1991: 382]. Determining the actual function and parameters to use is made easier by the use of computer software like Logical Decisions© [1993].

Logical Decisions© allows the decision maker to customize a utility function by manipulating a graphical representation. The decision maker can make adjustments to the graph until he or she is satisfied that it represents his or her beliefs. For this model, the decision maker uses a best, worst, and target value. The DA model provides the best and worst case simply by calculating the best and worst outcomes using both cost and time. The target value comes from the input to the life-cycle cost module, regulations, or contracts. These three values determine the basis for the utility function and the decision maker can then change the shape of the graph until satisfied with its accuracy.

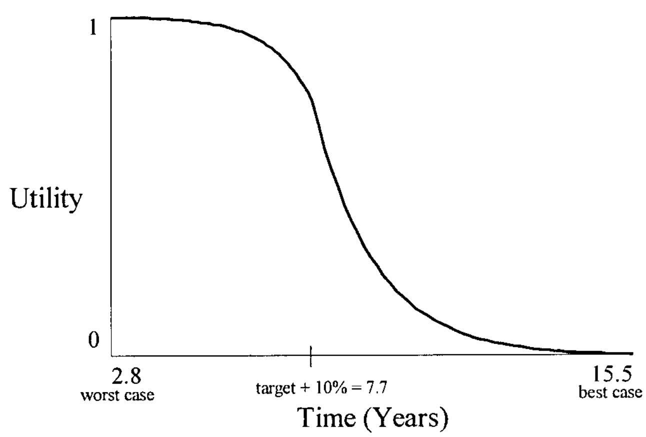


Figure 3.7 Example Attribute Utility Curve

Using the recommendations from the Landfill Stabilization Focus Area, a general utility function shape was determined. The best case outcome has the highest utility (1) and the worst case has the lowest utility (0). DOE has a high utility for costs and times that are below the target value plus a 10% error factor. On the other hand, the DOE has very little utility for costs and times that exceed this value [Geiger: 1995]. This philosophy results in a utility function similar to the graph shown in Figure 3.7.

The utility function in Figure 3.7 was developed in Logical Decisions©. It uses the best and worst case for the endpoints, and assigns a utility of 0.75 to the target value plus 10%. The midpoint utilities for the two sections, 0.875 and 0.375, are then assigned to values. The target value of 7 years was assigned a utility of 0.875, and the target value plus 25% (7*1.25 = 8.75) was assigned a utility of 0.375. Using a 3-point heuristic such as this enables a utility function to be formulated from the three known values. Logical Decisions© can then produce the functional form of the utility curve. The exponential function, which was discussed in Chapter 2, is used to form the curves between the endpoints and the midpoints. The formula for the utility function in Figure 3.7 is given in Equation (3.1).

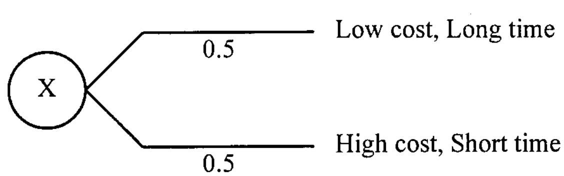
$$U_x(x) = 1.002 - 0.0001348e^{0.9784x} \qquad \text{for } x < 7.7 \tag{3.1}$$

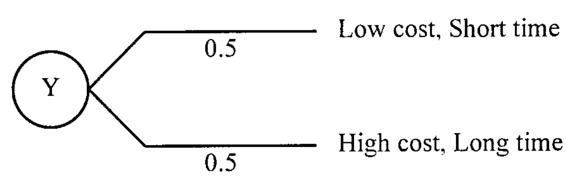
$$U_x(x) = -0.004582 + 116.4e^{-0.6544x} \qquad \text{for } x \geq 7.7$$

where $U_x(x)$ is the utility of a strategy requiring x years

Once this function is known, it can be input into the DA model and used to choose technology strategies based on the highest utility. A similar function is developed for the cost attribute. This function can also be calculated using a best case, worst case, and target values. A 3-point heuristic like the one used for the time attribute makes the formulation simple. When the utility functions for both attributes are determined, they can be combined in one objective function using parameters to represent the importance of each attribute. The additive objective function discussed in Chapter 2 is used to combine the utility functions for cost and time.

3.2.2.2 Objective Function. Before using an additive value function as suggested, tests for independence must be done to ensure that the two attributes exhibit additive independence. Two attributes are additively independent if preferences for lotteries in one attribute do not depend on the other attribute. For this model, the decision maker must be indifferent to the following lotteries X and Y:





If this condition holds for both attributes, then the decision maker's objective function can be represented by an additive value function [Keeney and Raiffa, 1976: 109-111]. If this is the case, then a parameter, k, is used to represent the decision maker's preference between the two attributes. This simple additive form is shown in (3.2).

$$U(x,y) = kU_x(x) + (1-k)U_y(y) \tag{3.2}$$

where: $U(x,y)$ is the total utility, $U_x(x)$ is the utility for a cost x, $U_y(y)$ is the utility for a time y, and k is the weight given to cost

For the DOE, cost and time are treated as independent attributes. Based on discussions with the DOE and MSE, cost and time satisfy the condition of additive independence provided that constraints are met [Geiger: 1995] [Antonioli: 1996]. Therefore, when cost and time are less than the maximum constraint values, the decision maker should feel indifferent to the lotteries of one attribute, regardless of the other attribute. This makes cost and time mutually preferentially independent, and thus allows an additive value function to be used as the objective function. Some decision makers, however, may argue that cost and time are not independent. Even without additive independence, the additive utility function can be used as a baseline approximation [Clemen, 1991: 483]. Along with this, the additive utility function can provide good results even when more complex models provide a better representation of the decision maker's preferences [Stewart, 1995: 256].

To use the additive value function, the weight parameter (k) must be determined. This weight can represent the decision maker's preference toward one of the attributes. If k is forced to fall between 0 and 1, then (1-k) can be used for the weight of the other attribute. This model uses k as the weight for cost.

Software, such as Logical Decisions©, can be used to help a decision maker determine k. Logical Decisions© uses a sliding bar that allows the user to determine k by sizing bars which represent the importance of each attribute. However, with only two

attributes the value can usually be easily determined. If cost is twice as important as time, then k = 0.667 and (1-k) = 0.333. Regardless, once the complete additive value function is developed, it must be input into the DA model. This objective function is then used to select the technologies.

When the model uses this value function as the objective function, technology strategies are selected based on how well they meet the decision maker's assessment of cost and time. The strategy's total cost and time is still calculated in the model, but these values are then transformed into utility using the objective function. Therefore, the strategy with the highest expected utility is the one that should be optimal for an expected value decision maker.

3.2.3 Modeling Assumptions. Certain assumptions were made in order to assemble the DA model. These assumptions are listed and followed by an explanation:

1) Considered technologies are applicable to the given waste site
2) Cost and time distributions are modeled using the gamma distribution
3) The decision to stabilize is made before running the model

The first assumption requires that all of the technologies used in the model be applicable to the given waste site. This assumption is important because the DA model does not eliminate technologies that cannot be used for specific sites and waste streams. The validity of this assumption greatly depends on the preliminary site characterization, which must be done in order to determine which technologies are applicable. If this

initial characterization is incorrect, then the technologies used in the model may not be appropriate.

The next key assumption is that the cost and time values for O&M and R&D follow gamma distributions. If life-cycle cost and time data is available, then a more precise distribution and parameters can be calculated from this sample. When the actual LCC data is produced, the data can be fitted to an empirically best distribution, which may not necessarily be a gamma distribution. If the gamma distribution is more applicable, however, then the parameter values can be determined using the actual LCC sample data. The gamma distribution was chosen, however, because: 1) The gamma function masses the probability near the mean, but it also has a right-hand tail that allows for greater values. This shape is a reasonable representation for contract situations, where the time and cost involved is very likely to meet or exceed the deadline, but not likely to be extremely under-budget or ahead of schedule. 2) The gamma function is always nonnegative, which is necessary for cost and time variables. 3) The gamma distribution uses only two parameters which allow the shape to be changed to fit different needs. 4) The sum of independent gamma distributions is a gamma distribution.

It should be noted that the model can support the use of any of 21 common distributions, provided the appropriate parameters are calculated. In order to use gamma distributions, the parameters must be determined. The data that is input into the model provides only the mean and standard deviation for cost and time. The parameters for the

gamma distribution are the shape and scale parameter. The density function for the gamma distribution is given in (3.3).

$$\mathrm{f}(x) = \left(\frac{\beta^{\alpha} \cdot x^{\alpha-1} \cdot e^{-x \cdot \beta}}{\Gamma(\alpha)} \right) \quad \text{for } \mathrm{x} > 0 \tag{3.3}$$

where: shape parameter (α) > 0, and scale parameter (β) > 0, $\Gamma(\alpha)$ as defined on page 99 in Appendix G

In order to determine the parameters, α and β, the first two moments were used from the data to match to the first two moments for the gamma distribution. Although this only approximates the distribution, the maximum likelihood estimator equation is iterative and complex to solve. The iterative maximum likelihood estimator equations must be solved simultaneously. These equations can be found in Appendix H. Matching moments, however, provides an adequate representation for the distribution, especially given that only three states are used for each uncertain event in the DA model, which means that only the first two moments can be matched regardless. In order to show this relationship, an example mean and variance are given, and the moments are then matched to a gamma distribution in the DA model.

The following example uses the equations for the DPL© gamma distribution [ADA, 1995: 409]. The parameter values are not derived using the maximum likelihood estimator, therefore the parameter estimates are biased. However, the first two moments

are used to match the mean and variance for the gamma distribution, which provides a close approximation for the parameter values.

$$\text{For } \mu = 10 \text{ and } \sigma^2 = 4$$

$$\alpha = (\mu^2/\sigma^2) = 25 \text{ and } \beta = (\mu/\sigma^2) = 2.5$$

Using the given parameters, the DA model creates a discrete gamma distribution with three states. The example gamma distribution would generate the probability frequency graph, shown in Figure 3.8, to assign probabilities to discrete values. For this case, the discrete values of 7.3, 10.5, and 14.6, are assigned probabilities of 0.28, 0.63, and 0.08. This discrete distribution approximates the gamma distribution with the given parameters. Because the moments were matched to get the parameters, the mean and variance for the approximated distribution are identical to the input values for the mean and variance. Therefore, the mean of the gamma distribution for this example remains 10, and the variance remains 4.

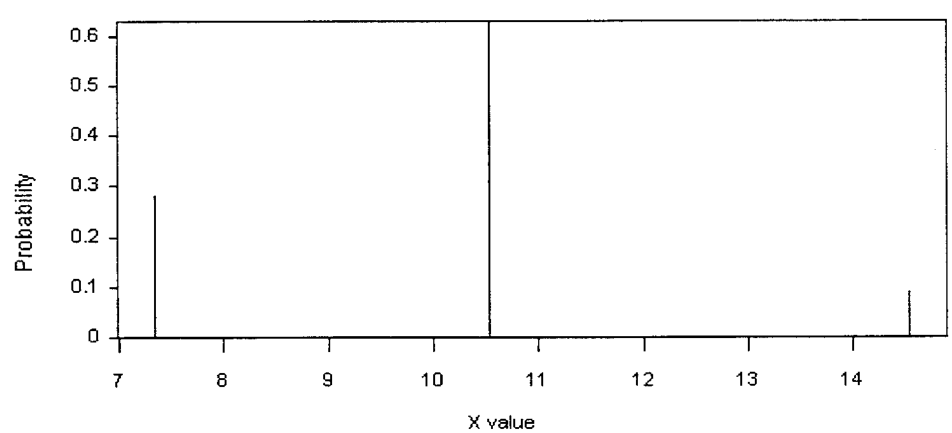


Figure 3.8 Frequency Graph for Example Gamma Distribution

Another key assumption requires that the decision to stabilize be made before the model is run. The decision to stabilize a waste site is dictated by environmental issues. As directed by DOE, this model does not account for environmental issues, therefore, the model is not set up to determine if stabilization is necessary. If stabilization is required, then the user must reflect this in the model. This can easily be done by controlling the path in the decision tree. Along with this, the model assumes that the technologies are input in accordance with the stabilization decision. Therefore, if stabilization is used, the other technologies in the model should be compatible with stabilized material.

3.2.4 Data Structure. The data that is used in the DA model is stored in a spreadsheet which is linked to the model. The data for each technology is generated by a life-cycle cost model simulation of the cost and time elements. The data for the technologies, which is input into the spreadsheet, consists of the mean and standard deviations for the cost and time simulated distributions. The spreadsheet for the example used in this study allows three technology choices for each of the 7 processes, but there is no limit to the number of technologies available for each process. The data set for this analysis is shown and explained in Appendix I. The values given were taken from DOE literature, technology principle investigators, and MSE estimates. These values are not attributable and are only used to demonstrate the DA model's capabilities.

IV. Analysis of Results

4.1 Introduction

The analysis of the DA model and technology data is presented using four analysis scenarios. The scenarios include a typical analysis of the given data to determine the best overall remediation strategy, a scenario to compare treatment and containment options, and a similar scenario to compare technology choices for a single process. In each case, the alternatives are compared on the basis of total cost, total time, and utility to the decision maker. The risk (cost, schedule, and implementation) has been implicitly considered for all technologies through the use of individual utility functions.

Table 4.1

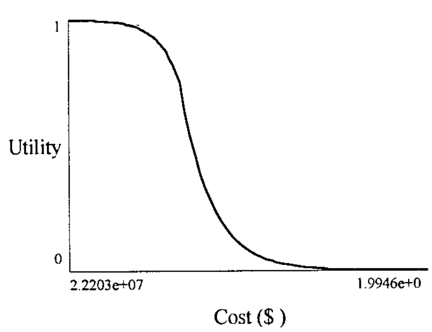
	Overlap	Stop_Time	Fix_Cost	Fix_Time
Characterization	0%	100%	$34,687.33	0.03724 yrs
Stabilization	0%	100%	$21,685,186.67	0.88877 yrs
Retrieval	90%	25%	$17,833,333.33	0.656917 yrs
Treatment	100%	25%	$43,317,900.00	2.812497 yrs
Disposal	100%	10%	$29,330,333.00	0 yrs
Containment	0%	50%	$6,923,633.33	0.83333 yrs
Monitoring	N/A	10%	$243,809.00	0 yrs

The scenarios use the same values for most of the variables in the DA model. These constant values are listed in Table 4.1, and any changes are explained in the analysis for each scenario. The values in the table are estimates from the DOE and MSE [Geiger, 1995][Antonioli, 1996]. As discussed in Appendix E, the Overlap variables represents the percentage of overlap between processes, and the Stop_Time variables

represent the proportion of O&M until technology failure. The Fix_Time and Fix_Cost values represent the average O&M cost or time of the technology choices for each process, and are used as penalties in the case of technology failure.

4.2 Utility Functions

In order to compare the alternatives, a set of utility functions for cost and time are determined using the 3-point heuristic described in Chapter 3. The DA model can determine the best and worst case values of cost and time. The best case values are assigned the 5th percentile of the cost and time distributions, while the worst case values are assigned the 95th percentile. These values, along with target estimates, provide sufficient information to form the individual attribute utility functions. Because of the different analysis scenarios, the utility functions were calculated for a stabilized remediation strategy and for a strategy without stabilization. The graphs of the utility functions are given in Figure 4.1a-b. The values used for these functions are shown with the graphs and formulas in Appendix J.



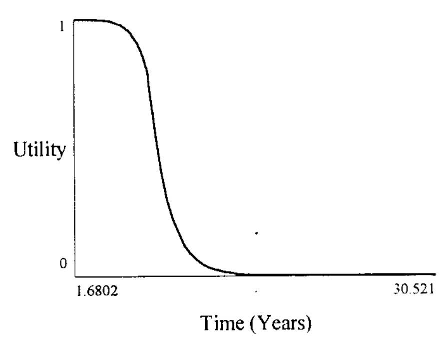


Figure 4.1a Attribute Utility Functions With Stabilization

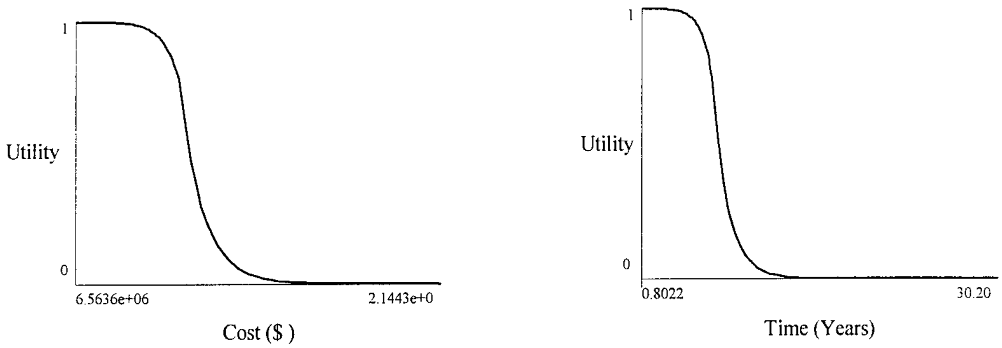


Figure 4.1b Attribute Utility Functions Without Stabilization

For each scenario the weight given to cost is (k=0.6667). This translates to cost being twice as important to the decision maker as time. This assumes however, that the remediation strategy does not exceed the limiting values for total cost and time (Max_Cost, Max_Time). For each scenario, the maximum cost is $100,000,000.00 (Max_Cost = 100,000,000), and the maximum time constraint is 10 years (Max_Time = 10). If a strategy exceeds one of these values it is given a utility value of zero. The resulting objective function is given in (4.1)

$$\text{If (Total\_Cost} \leq \text{Max\_Cost and Total\_Time} \leq \text{Max\_Time) then,} \tag{4.1}$$

$$\text{Utility(strategy)} = 0.6667 * \text{U(Total\_Cost)} + 0.3333 * \text{U(Total\_Time) else,}$$

$$\text{U(strategy)} = 0$$

4.3 Scenario 1: Complete Strategy Analysis

The first scenario involves analyzing the complete remediation process. The scenario is designed to approximate a decision maker's need to determine a complete remediation strategy for the INEL test pit 9. The DA model is will help the decision

maker select the best remediation strategy for this scenario using the applicable technology choices for each process given by MSE. For this scenario, it is assumed that the site requires stabilization. Therefore, the utility functions shown previously in Figure 4.1a are used to compare the alternatives. These functions are also explained in Appendix J.

Using the information above, the DA model calculates the optimum remediation strategy for this scenario. Although data for actual technologies are used, strategies are represented in this analysis using the following notation:

XX-Y, XX-Y, XX-Y, ...

Where XX = (CA: Characterization, S: Stabilization, R: Removal, T: Treatment, D: Disposal, C: Containment, M: Monitoring)

and Y = (1: Technology1, 2: Technology2, 3: Technology3)
(The names and data for the technologies can be found in Appendix H)

The strategy with the highest utility value for this scenario is (CA-1, S-1, C-1, M-2). This optimal strategy has a utility expected value of 0.991879. Although this strategy yields the highest expected utility value, there is relatively no difference between strategy 1 and 2, and little difference in any of the top five strategies. The best five strategies based on utility are listed with their expected values for utility, cost, and time in Table 4.2.

Table 4.2

Strategy	Utility	Cost	Time (Yrs)
1) CA-1, S-1, C-1, M-2	0.991879	$43,390,028	1.6641
2) CA-2, S-1, C-1, M-2	0.991811	$39,067,517	3.9754
3) CA-3, S-1, C-1, M-2	0.985656	$39,068,263	4.9624
4) CA-2, S-1, C-3, M-2	0.970137	$49,565,961	4.8062
5) CA-3, S-1, C-3, M-2	0.969249	$49,811,968	5.1039

As shown in the table, the resulting time and cost values for the strategies vary despite the similar utility values. The optimal strategy, (CA-1, S-1, C-1, M-2), has an expected cost $4 million higher than the next best strategy, (CA-2, S-1, C-1, M-2). However, the expected time for the optimal strategy is 2.5 years lower than the other alternatives. Despite the weight given to cost in the utility function, the value for time significantly influences the outcome. This is due to the attribute utility functions and the resulting values for cost and time. There is very little difference, according to the decision maker's utility function for cost, in the resulting cost values for the above strategies. The time values, however, are significantly different in terms of utility to the decision maker.

Figure 4.2 shows the plot of the cost and time values of the feasible strategies for the scenario. Feasible strategies are those strategies that have compatible technologies and have cost and times below the maximum constraint values of $100,000,000 and 10 years. Only feasible strategies are shown on the graph in Figure 4.2. The dashed line shows the target values for cost and time. The top five strategies discussed above, which have the highest utility values, are numbered on the plot. These strategies make up the majority of the strategies within the target region for both cost and time. Figure 4.3 shows that the strategies with the lowest time values yield the highest utility values. There are other groups of strategies that have lower values for cost, but these strategies have much lower utility due to the significant increase in time. Most of the strategies have cost values below the cost target of $70,000,000. Very few strategies, however,

have time values below the time target. Therefore, the sensitivity to cost is decreased and time becomes influential. This fact is made clear in Figure 4.3. Figure 4.3 shows that all of the strategies have similar value for the utility of cost. The utility of the time values then provides the only means to distinguish the strategies.

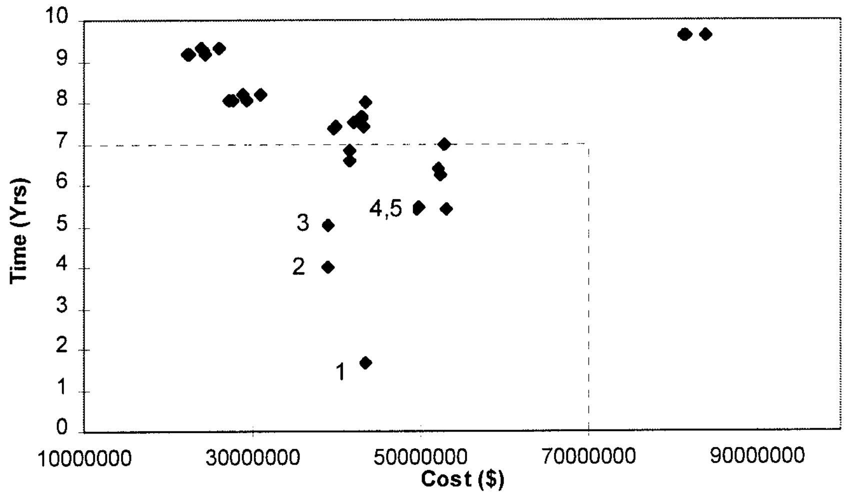


Figure 4.2 Cost and Time Plot for Scenario 1 Strategies

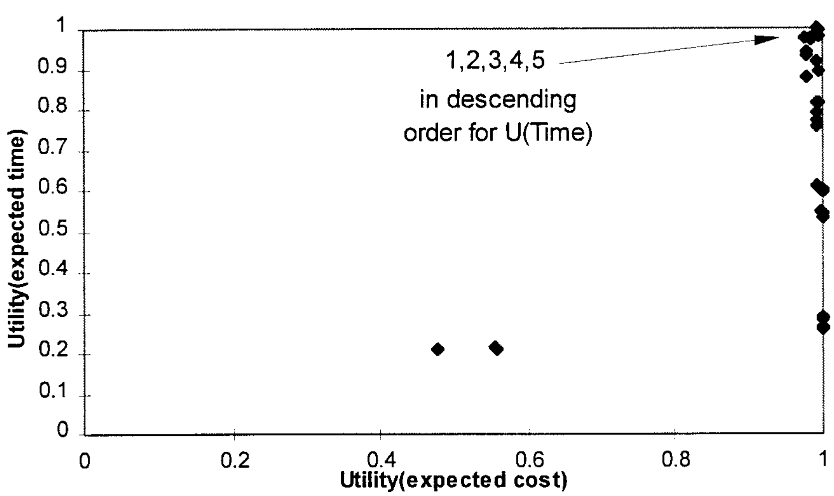


Figure 4.3 Utility Plot for Scenario 1

The primary differences in the strategies with the highest utility values are in the characterization and the containment technologies used. The technologies used in the optimal strategy are all currently available and require no R&D. The characterization technology changes in each of the top three strategies. The results imply that the solutions are insensitive to the characterization technology used. This is expected, however, because of the relatively small costs and times required by the characterization technologies. Using a characterization technology that is not currently available and requires R&D can save approximately $4 million. This savings is due to the time value of money, which increases the remediation time by more than 2.5 years. This increase in time is what causes the utility to decrease. The change in utility of $39 million and $43 million is 0.003, while the change in utility from 2.6 years to 4.5 years is 0.01. The increase in time is 3 times as bad as the increase in cost.

For all of the top five strategies, the optimal stabilization technology is always S-1. If another stabilization technology is chosen, the best possible utility value drops to less than 0.8, significantly less than the previously discussed options. The containment technology varies slightly among the top five strategies. Containment technology C-1 is the optimal choice, but C-3 is used in strategies with utility values of 0.97.

The previous results were based solely on expected utility, where utility is based on cost and time. Examining the distributions of these values provides insight into the risk involved in each strategy. Figure 4.4a shows the cumulative distribution of utility for the top five remediation strategies. These distributions follow the results of the expected

value of utility. The top three strategies: (CA-1, S-1, C-1, M-2), (CA-2, S-1, C-1, M-2), and (CA-3, S-1, C-1, M-2) stochastically dominate the remaining two options. Stochastic dominance implies that these strategies are more likely to have higher utility values than the other strategies.

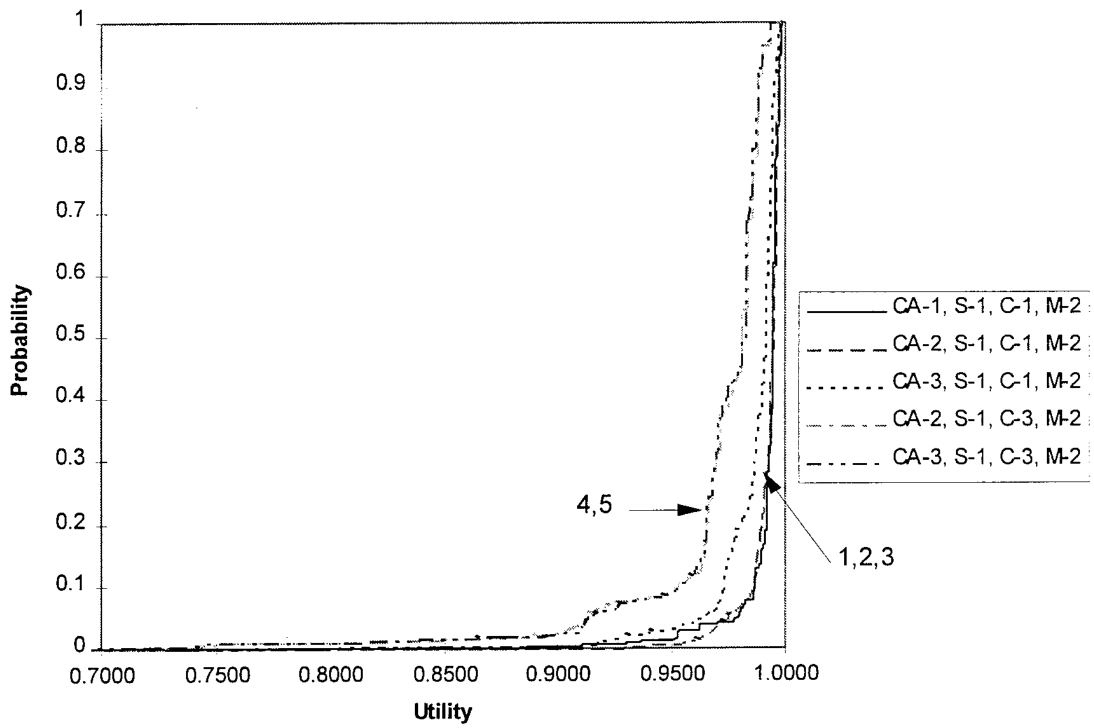


Figure 4.4a Cumulative Utility Distributions for Scenario 1

The lower utility values occur when several technologies in the strategy fail, while the higher utility values occur when none of the technologies fail. Despite the limited range of the graph, the fifth strategy (CA-3, S-1, C-3, M-2) has a 0.2% chance of exceeding the maximum values for cost and time. Therefore, this strategy results in a

utility of 0 with probability 0.002. As in Chapter 3, if a strategy exceeds one of these limiting values, it is given a utility of zero.

The cumulative cost graph in Figure 4.4b shows that the second and third strategies, which had the lowest expected cost, stochastically dominate all others. However, the optimal strategy stochastically dominates the fourth and fifth strategies. The cumulative time distributions in Figure 4.4c show that strategy (CA-1, S-1, C-1, M-2) stochastically dominates all others for total time. This strategy also deterministically dominates all other strategies except for the strategy (CA-2, S-1, C-1, M-2). This dominance implies that the worst possible value for time with strategy (CA-2, S-1, C-1, M-2) is always better than the best possible time values for the other three strategies. This result supports the expected value results.

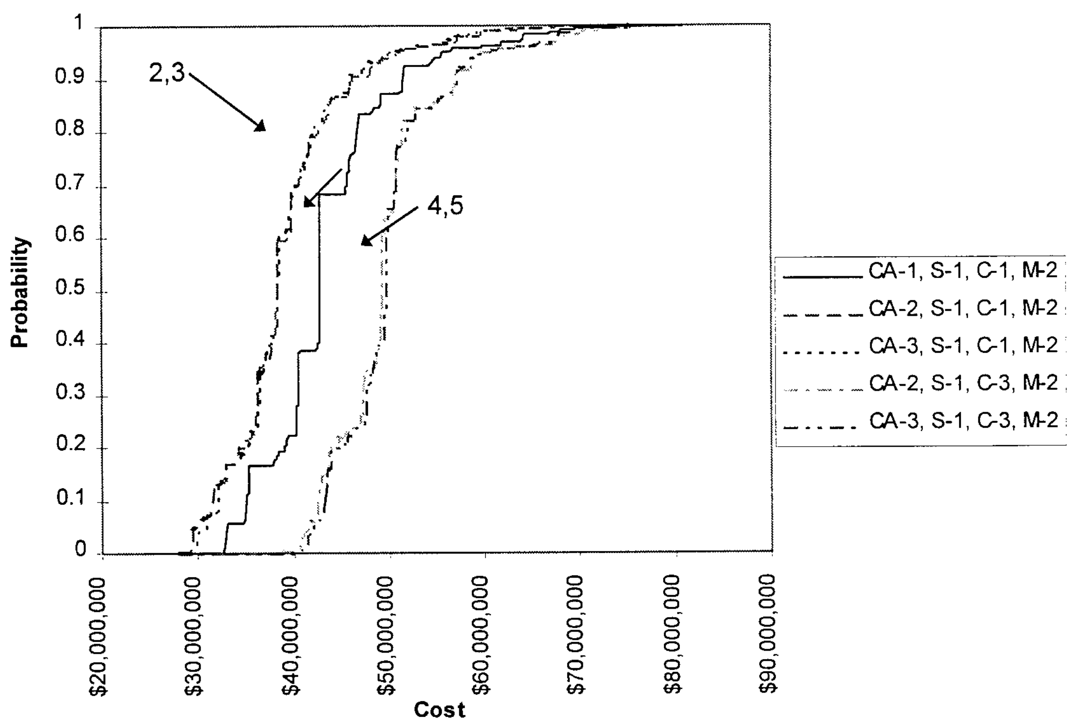


Figure 4.4b Cumulative Cost Distributions for Scenario 1

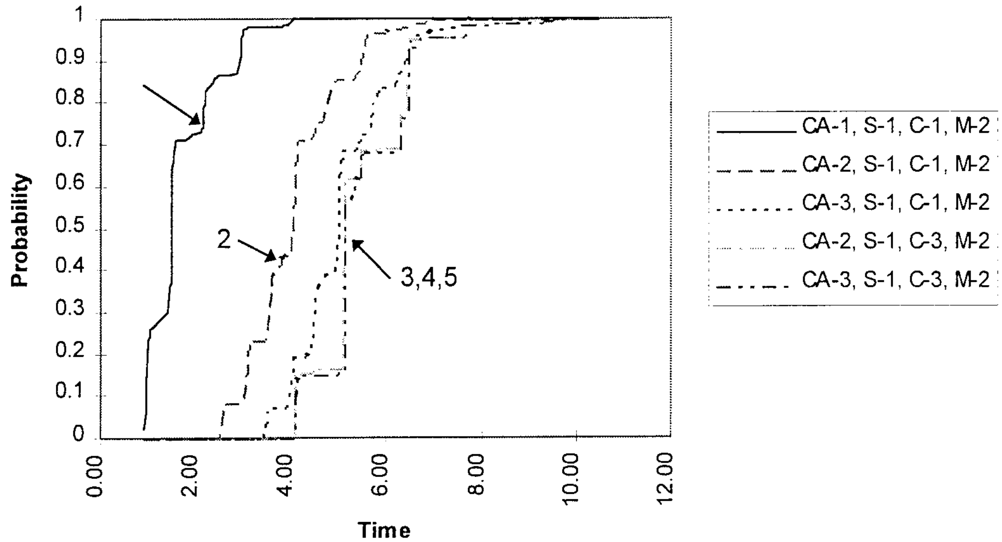


Figure 4.4c Cumulative Time Distributions for Scenario 1

The frequency distributions for cost and time also illustrate the risk inherent in each strategy. Graphs of the frequency distributions of cost and time for the five strategies are given in Appendix K, and indicate the same results. The statistics for the frequency distributions are shown in Table 4.3. The sample variance values give an estimate of the risk for each strategy. The optimal strategy has the lowest average time value and the smallest sample variance, which implies that the risk in remediation time for this strategy is low. The cost of the optimal strategy, however, involves more risk. Not only is the expected cost higher than the next two strategies, but the sample variance of the cost values is larger than the other options. The cumulative cost distribution from Figure 4.4b shows that about 99% of the time this strategy has a cost less than the target cost of $70,000,000.

Table 4.3

Strategy	Cost $\overline{X}$ ($ Million)	Cost S^2 ($ Million)^2	Time $\overline{X}$ (Yrs)	Time S^2 (Yrs)^2
CA-1, S-1, C-1, M-2	43.390	47.7	1.664	0.477
CA-2, S-1, C-1, M-2	39.067	39.8	3.975	0.874
CA-3, S-1, C-1, M-2	39.068	36.1	4.962	0.873
CA-2, S-1, C-3, M-2	49.565	36.7	4.806	1.294
CA-3, S-1, C-3, M-2	49.811	32.9	5.103	1.070

The optimal strategy for the given utility function weights for cost and time utility is (CA-1, S-1, C-1, M-2). Although the total cost for this strategy is slightly higher than other choices, this strategy requires significantly less time than all other alternatives. This difference in remediation time makes up for the slightly higher cost. This result may seem to contradict the importance given to cost (k=0.6667), but this follows the previous conclusions concerning the range of the cost and time values and the range of the resulting utility values. As discussed, any of the three characterization technologies can be used with (S-1, C-1, M-2) and cause little change in utility to the decision maker. Other changes to this strategy can be made but with significantly decreased utility.

Further sensitivity analysis shows the optimal policy's sensitivity to the variable values used in the model. The rainbow diagram in Figure 4.5 shows how the optimal policy changes as the cost utility weight increases. The technologies selected for the optimal strategy are relatively insensitive. Only the optimal characterization technology choice changes as cost becomes more important to the decision maker. The policy changes occur at approximately k=0.68 and k=0.925. The similar results for CA-1, CA-2, and CA-3 are also evident in this graph. The optimal policy given above is for

k=0.6667, which is in the region of the rainbow diagram where policy changes begin to occur.

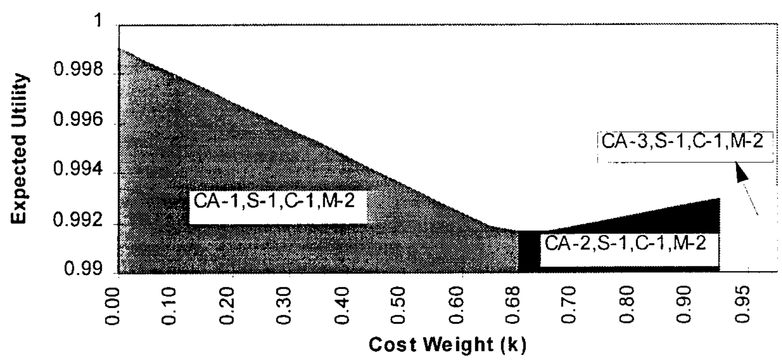


Figure 4.5 Rainbow Diagram for Cost Utility Weight in Scenario 1

The effects of changing other variable values are shown in Figure 4.6. This tornado diagram indicates the most influential variables. The most significant variables are at the top of the graph and have the longest bands. The variables with the shortest bands, at the bottom of the graph, are the least influential.

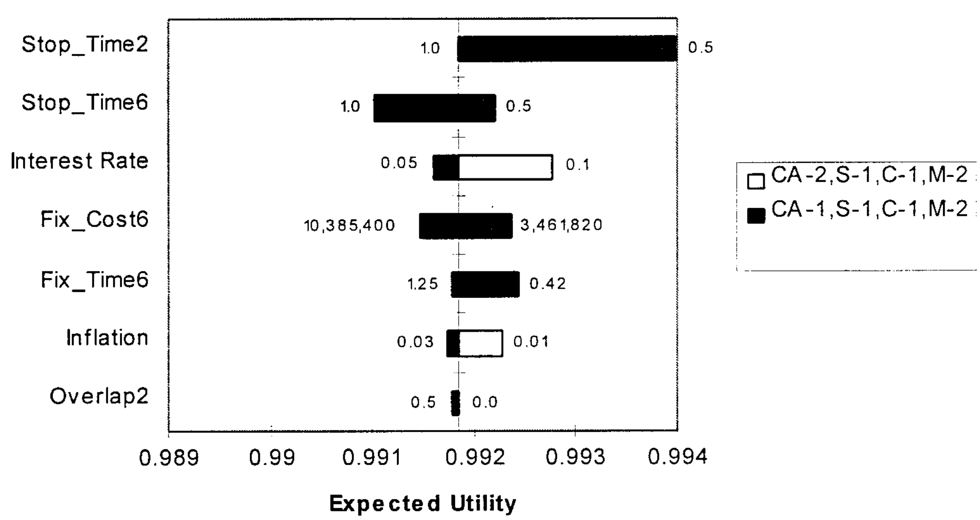


Figure 4.6 Tornado Diagram for Scenario 1 Optimal Decision Policy

To perform the sensitivity analysis, the values for most of the variables were changed significantly from their nominal settings. Unless a range was specified, the values were varied from 50% to 150%. These ranges represent realistic values, however, especially for variables like the penalties for technology failure and the Stop_Time variables. Even with the wide range of values, the largest magnitude of change in the utility of the solution is 0.002. Regardless, the tornado diagram indicates which variables are important to this solution. The diagram shows that the variables for containment and stabilization technology failure are influential to this solution, as well as the interest and inflation rates.

The only changes to the optimal policy occur when the interest rate is increased or when the inflation rate is decreased. This result follows the time value of money calculations used in the model. The CA-2 technology requires R&D, which allows other technology costs to be incurred at a later time. Therefore, if interest rates increase or the inflation rate decreases, it would be preferable to delay the costs and thus (CA-2, S-1, C-1, M-2) would be preferred to (CA-1, S-1, C-1, M-2).

4.4 Scenario 2: Comparison of Treatment and Containment

In scenario 2 it is assumed that the preliminary site characterization of the INEL pit 9 has determined that a specific characterization technology, CA-2, must be used. Added to this, it has been determined that stabilization of the waste is not required. Based on this, the decision maker must decide whether to treat or contain the waste site and which strategy to use. The comparison of treatment and containment options is a key issue for the DOE, which makes this a likely analysis situation. Most of the same

variable values are used for this scenario. The primary difference is the change in the utility functions due to the lack of stabilization. The utility functions used for this analysis were previously shown in Figure 4.1b, and are also explained in Appendix J. The weight for the utility of cost is (k=0.6667).

To compare treatment and containment strategies, the optimal strategy for each method is determined. Treatment strategies consist of a retrieval, treatment, and disposal technology, while the containment technology makes up the containment strategy. For each strategy, monitoring technology M-2 is used. This is done because this is the only monitoring technology that is compatible with both treatment and containment options. Also, this technology clearly dominates the other monitoring alternative. This can be shown by examining the technology data in Appendix E. On-site disposal and monitoring (D-2, M-2) clearly dominates off-site disposal and monitoring (D-1, M-1). Selecting the monitoring technology determines the disposal technology, D-2, because of compatibility restrictions.

For this scenario, the optimal treatment strategy is (R-1, T-1, D-2). This strategy has an expected utility of 0.989413. The optimal containment strategy for this scenario is (C-1) with an expected utility of 0.99381. As in scenario 1, the utility values for the strategies are extremely high, and different strategies provide similar results. The top five strategies, along with their expected values for utility, cost, and time, are given in Table 4.4.

Table 4.4

Strategy	Utility	Cost	Time (Yrs)
1) CA-2, C-1, M-2	0.99381	$6,566,594	3.6788
2) CA-2, R-1, T-1, D-2, M-2	0.989413	$17,021,437	3.1328
3) CA-2, R-2, T-1, D-2, M-2	0.987297	$18,946,733	3.2347
4) CA-2, C-3, M-2	0.96168	$17,013,336	4.7833
5)CA-2, R-1, T-3, D-2, M-2	0.957239	$10,238,361	5.1994

The data in the table shows that remediation time is very influential despite the weight given to cost. The optimal strategy for expected utility costs $11 million less than the next best strategy, but the utility values are close because the optimal strategy takes 0.5 years longer. As in Scenario 1, this result is partly due to the utility functions and the cost and time values for the strategies. There is little difference to the decision maker in $6 million and $17 million, but the difference in 3.68 years and 3.13 years makes strategy (CA-2, R-1, T-1, D-2, M-2) have a lower utility than strategy (CA-2, C-1, M-2). Added to this, (CA-2, R-1, T-1, D-2, M-2) is a treatment strategy which has greater opportunity for technology failure due to the additional technologies involved. When technologies fail, the utility for the strategy decreases significantly.

The graph in Figure 4.7 plots the cost and time values for the feasible strategies for this scenario. Only those strategies with cost and time values below the constraints of $100,000,000 and 10 years are shown. The target values for this scenario are shown by the dotted line. Generally, the graph shows that some strategies with lower costs and higher times have lower utility values. As in Scenario 1, the ranges for cost results in a small range for cost utility, but the range for time results in large range for time utility.

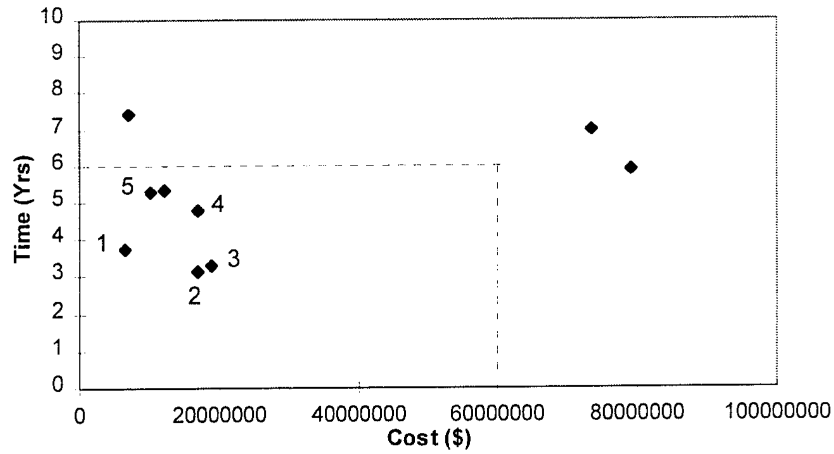


Figure 4.7 Cost and Time Plot for Scenario 2 Strategies

The cumulative distributions for utility, cost, and time illustrate the importance of time and show the dominance of some strategies. The cumulative distribution for utility is given in Figure 4.8a. This graph shows that the top three strategies stochastically dominate the fourth and fifth ranked strategies.

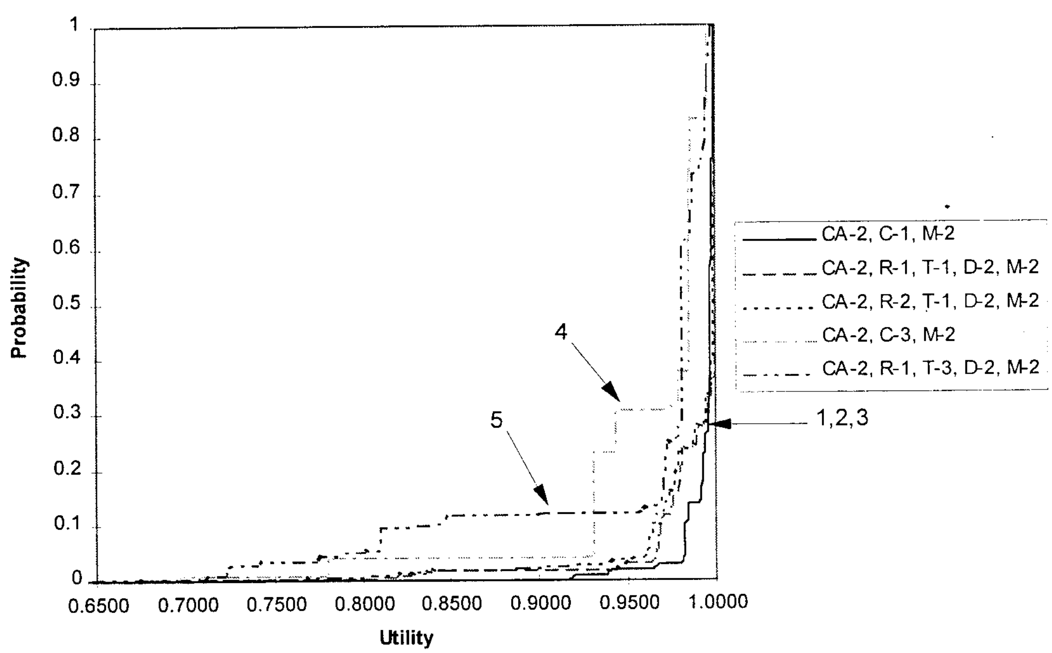


Figure 4.8a Cumulative Utility Distributions for Scenario 2

The cumulative distribution for cost, in Figure 4.8b, shows a much different result. The strategies (CA-2, C-1, M-2) and (CA-2, R-1, T-3, D-2, M-2) stochastically dominate the other alternatives, except for (CA-2, C-3, M-2). However, (CA-2, C-1, M-2) deterministically dominates strategy (CA-2, C-3, M-2), which means this strategy will always cost less than the other. The cumulative distributions for time, given in Figure 4.8c, show that the top three strategies stochastically dominate the remaining options.

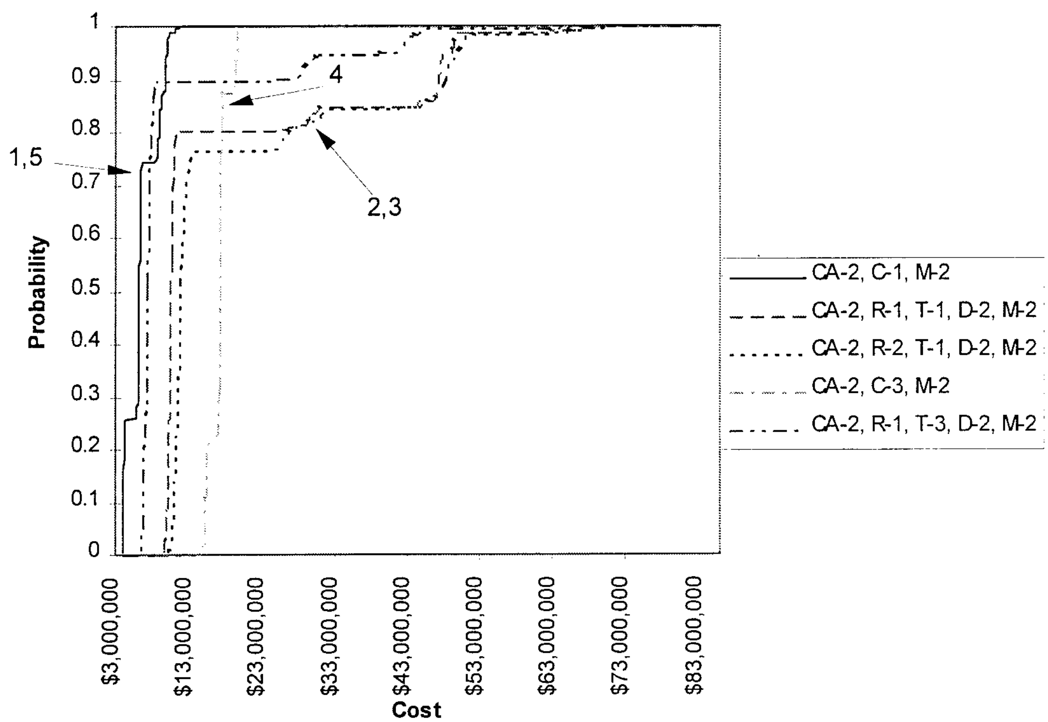


Figure 4.8b Cumulative Cost Distributions for Scenario 2

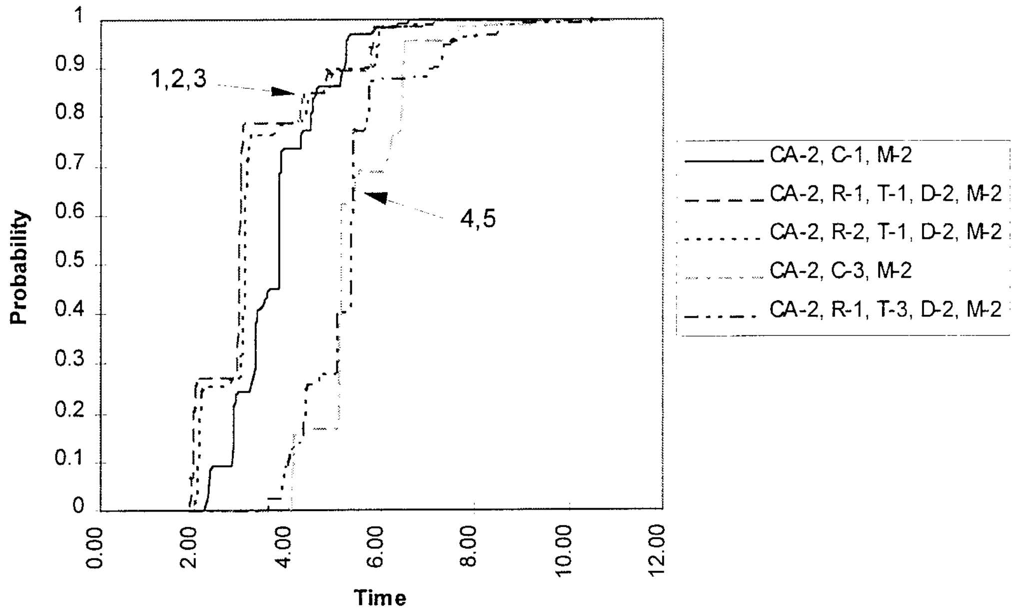


Figure 4.8c Cumulative Time Distributions for Scenario 2

Regardless of the utility values, there does not appear to be an obvious optimal strategy for this scenario. The strategy with the highest expected value for utility (CA-2, C-1, M-2) is a containment strategy which has the lowest expected cost. The strategy with the lowest expected time (CA-2, R-1, T-1, D-2, M-2) is a treatment strategy. Both of these options incorporate currently available technologies. The results for remediation time are very close for the top three strategies. The expected times for these strategies are within 6 months of each other. Examining the frequency distributions of cost and time for these strategies shows an important element of the risk in the strategies. The frequency graphs of cost and time for the top five strategies are shown in Appendix L. The statistics for these distributions are given in Table 4.5. The sample variance shows the risk inherent in each strategy's cost and time distributions. Strategies with smaller variance have less risk in the cost and time values.

Table 4.5

Strategy	Cost $\overline{X}$ ($ Million)	Cost S^2 ($ Million)^2	Time $\overline{X}$ (Yrs)	Time S^2 (Yrs)^2
CA-2, C-1, M-2	6.566	3.870	3.678	0.833
CA-2, R-1, T-1, D-2, M-2	17.021	200.0	3.132	1.425
CA-2, R-2, T-1, D-2, M-2	18.946	207.0	3.234	1.386
CA-2, C-3, M-2	17.013	1.46	4.783	1.310
CA-2, R-1, T-3, D-2, M-2	10.238	87.5	5.199	1.194

The data in the previous table implies that if the decision maker is willing to accept a higher average remediation time with some risk involved, then the containment strategy (CA-2, C-1, M-2) may be the best solution. The average cost of this strategy is always lower than most of the other options, and the variance of these values is comparatively low. The average time for this strategy averages 6 months longer than the second and third options, but the variance of the time values is the lowest of all strategies. Therefore, the decision maker can save $11 million with strategy (CA-2, C-1, M-2) if he or she is willing to accept the increase in remediation time. This results in a $22 Million per year trade-off between the two options. The decision maker can be confident in this strategy, however, because of the smaller variance in the cost and time values. In times of restricting budget allotments, such information could be critical in selecting a course of action.

Sensitivity analysis on this optimal policy shows that this solution is relatively insensitive to changes in the values of the input variables. The rainbow diagram in Figure 4.9 shows that the optimal policy remains (CA-2, C-1, M-2) unless the weight

given to cost is decreased to extremely low values. Specifically, if time is the only important factor then the optimal solution is (CA-2, R-1, T-1, D-2, M-2).

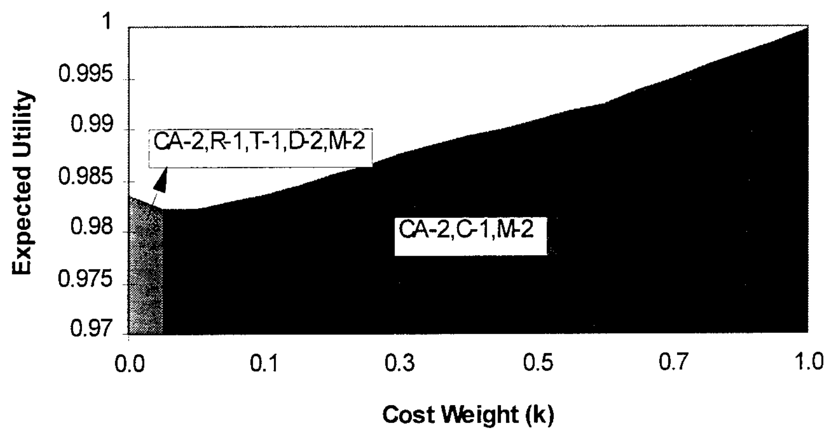


Figure 4.9 Rainbow Diagram for Cost Utility Weight in Scenario 2

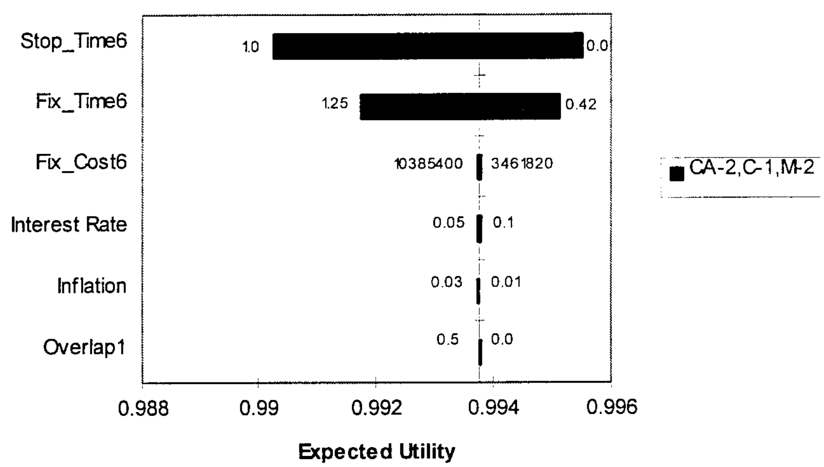


Figure 4.10 Tornado Diagram for Scenario 2 Optimal Decision Policy

The tornado diagram in Figure 4.10 shows that the variables for containment technology failure are the most influential to the expected utility of the optimal solution. The input variables were changed from 50% to 150% of their nominal values, unless a

more feasible range was specified. Despite the changes to the input variables, the optimal policy remains (CA-2, C-1, M-2).

4.5 Scenario 3: Single Process Technology Selection

The third scenario is examined to determine the best technology selection for a particular process. Scenario 3 assumes that the decision maker has determined that the waste site will be treated using the strategy (R-1, T-3, D-2, M-2), and stabilization is not required. Therefore, the decision maker must decide which characterization technology to use. Perhaps the optimal treatment strategy was found previously, but three new characterization technologies must now be compared. Because of the lack of stabilization, the same utility functions as Scenario 2 will be used. These functions were shown previously in Figure 4.1b, and are also explained in Appendix J.

Using expected utility the optimal technology selection is CA-1. The expected value for utility, cost, and time are given in Table 4.6. From this we see that CA-1 seems to dominate the other choices. It has a higher expected utility, a lower expected cost, and a lower expected time than CA-2 and CA-3. There is very little difference, however, between the values for expected utility, cost, and time for the three different strategies.

Table 4.6

Strategy	Utility	Cost	Time (Yrs)
1) CA-1, R-1, T-3, D-2, M-2	0.958492	$10,051,457	4.9022
2) CA-2, R-1, T-3, D-2, M-2	0.957562	$10,076,904	5.2076
3) CA-3, R-1, T-3, D-2, M-2	0.949342	$11,750,788	5.5921

The graphs in Figure 4.11a-c show the cumulative distributions of utility, cost, and time. These distributions prove how similar the three options are. There is no dominance evident in the cumulative utility graph because the distributions are similar. The utility values for CA-1 and CA-2, however, appear to be marginally higher than CA-3. The cumulative cost distributions for CA-1 and CA-2 are almost identical. The graph shows that about 70% of the costs for CA-1 and CA-2 are less than the best possible cost for CA-3. The cumulative time distributions in Figure 4.11c are also similar for all three characterization technologies. Again, the distribution for CA-1 shows that this strategy may result in less remediation time more often than the other options.

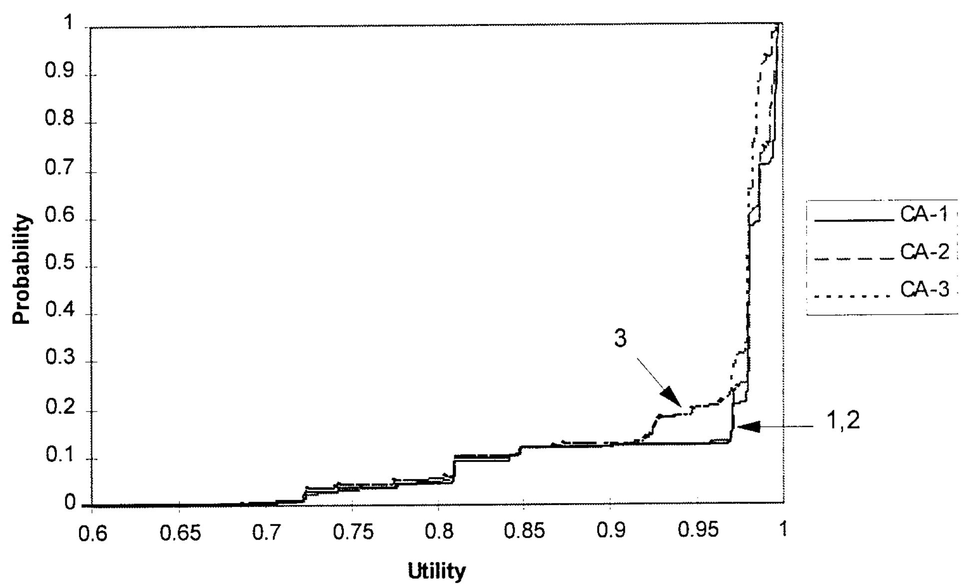


Figure 4.11a Cumulative Utility Distributions for Scenario 3

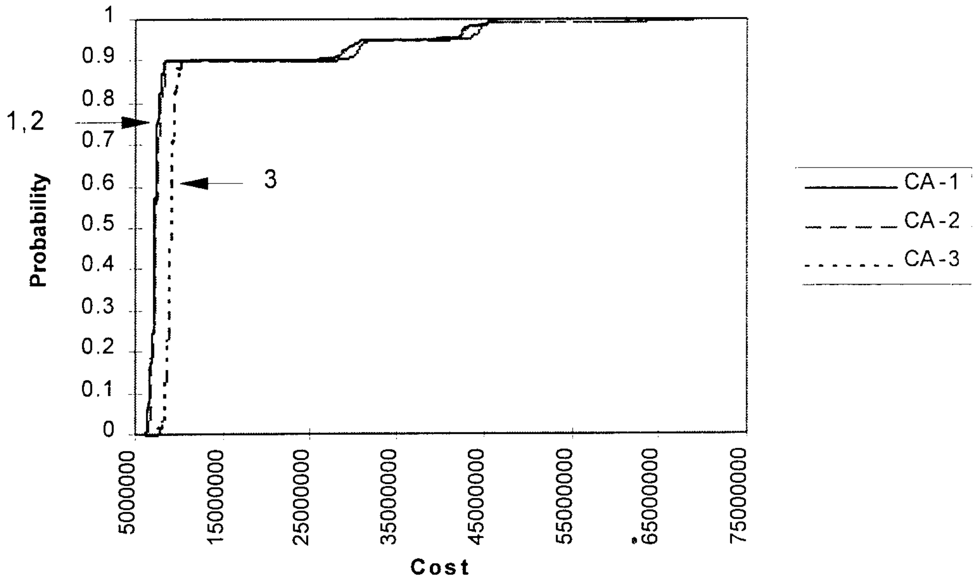


Figure 4.11b Cumulative Cost Distributions for Scenario 3

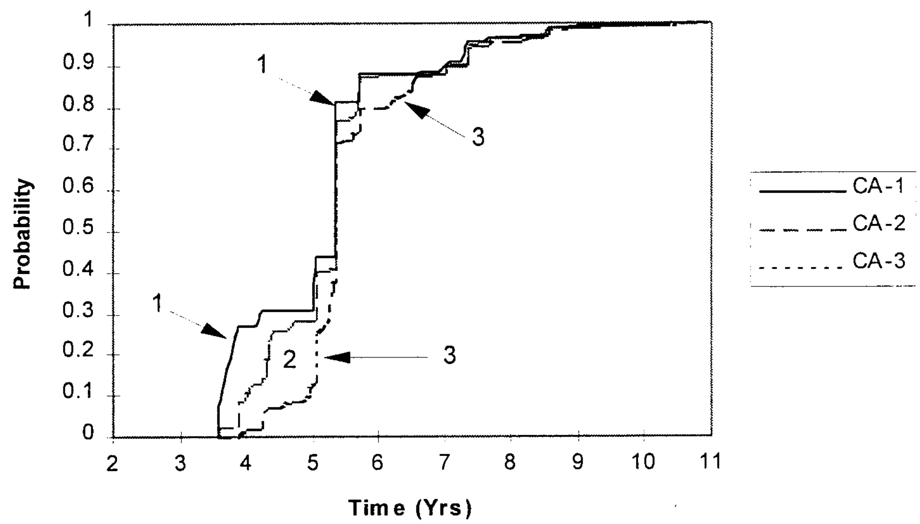


Figure 4.11c Cumulative Time Distributions for Scenario 3

Because of the similarities in these strategies, further analysis is necessary to distinguish an optimal decision policy. The frequency distributions determine the cost

and time risk for each technology. These distributions are given in Appendix M. The statistics for these distributions are shown in Table 4.7.

Table 4.7

Strategy	Cost $\overline{X}$ (\$ Million)	Cost S^2 (\$ Million)^2	Time $\overline{X}$ (Yrs)	Time S^2 (Yrs)^2
CA-1, R-1, T-3, D-2, M-2	\$10.051	\$83.7	4.902	1.476
CA-2, R-1, T-3, D-2, M-2	\$10.076	\$82.0	5.207	1.191
CA-3, R-1, T-3, D-2, M-2	\$11.750	\$81.2	5.592	0.995

The frequency distribution results show that CA-2 causes less variation in the cost and time for the strategy than CA-1. However, the maximum range of cost and time for CA-1 is less than or equal to the maximum value for CA-2. Based on this, it appears that characterization technology CA-1 should be used for the remediation strategy (CA-1, R-1, T-3, D-2, M-2). Most of the similarities in the results for the three technologies is due to the actual data for each technology. The O&M time for all three options is the same. The only difference is the R&D required for CA-2 and CA-3. The R&D time for these technologies has little effect on the expected time for the complete strategy. Along with this, most of the R&D cost for CA-2 and CA-3 is off-set by the R&D time. The R&D time allows retrieval and treatment to begin later, thus reducing the present value of the cost. On the other hand, CA-2 and CA-3 have a 10% chance of failing, while CA-1 is always successful. The probability of failure with technologies CA-2 and CA-3 makes up for the decrease in cost with a penalty cost for failure.

Similarities in the results could also be due to the fact that characterization accounts for a relatively small proportion of the total cost and time for the strategy, and

thus was given small penalties for technology failure. However, characterization is a very important part of the remediation process. Because of this, the penalties may actually be higher than the average values used for the analysis. CA-1, however, would be unaffected by any increase in penalty because the technology has a probability of failure of 0.

Sensitivity analysis shows how the optimal strategy of (CA-1, R-1, T-3, D-2, M-2) is insensitive to most changes in the input variables used. The rainbow diagram in Figure 4.12 shows that this strategy is optimal for almost all values of k. When the cost weight is close to one, meaning that cost is the only important attribute, the policy does change to (CA-2, R-1, T-3, D-2, M-2). This may seem contradictory to the expected value results, but the variance of the cost values causes the change. Further, the R&D from CA-2 allows other processes to begin later, and reduces the present value of the cost.

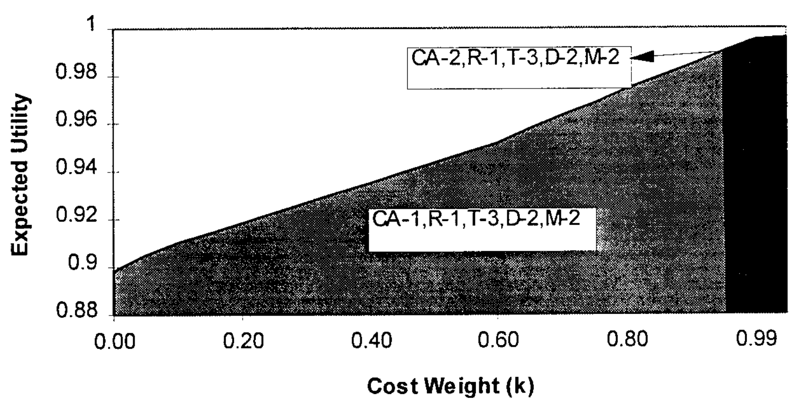


Figure 4.12 Rainbow Diagram for Cost Utility Weight in Scenario 3

The tornado diagram in Figure 4.13 shows that very few variable values affect the expected utility of the optimal decision policy. Changes in the interest rate, inflation rate, and overlap for characterization, produced only small changes in the expected utility value and did not result in an optimal policy change. This is expected because this scenario only examines the characterization technology choice.

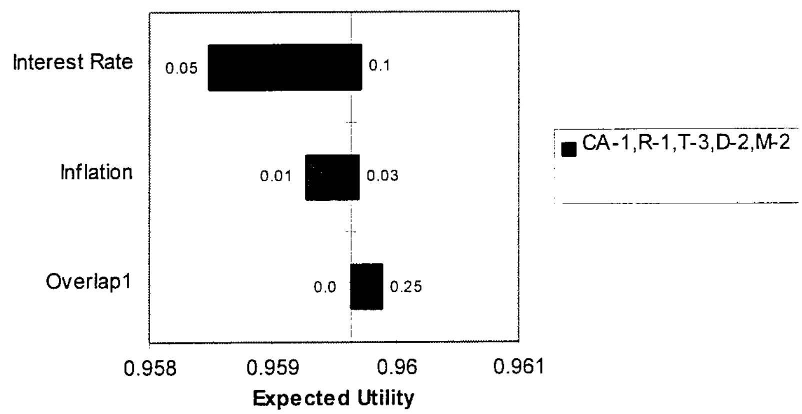


Figure 4.13 Tornado Diagram for Scenario 3 Optimal Decision Policy

4.6 Summary

Overall, the DA model provides many important tools for analyzing the technology selection decisions. The model uses the risk attitude of the decision maker to select technologies based on utility, however, cost and time data is also provided. The distributions for utility, cost, and time, provide valuable information to the decision maker. These distributions show the range and frequency of the values so that the decision maker sees the risk involved with each strategy. The model also allows for sensitivity analysis in the form of rainbow and tornado diagrams, for the input variable values. This tells the decision maker how sensitive the optimal policy is to change. The

previous scenarios outlined three of the probable analysis situations and showed how the model can be used to provide valuable information to the decision maker.

The common result throughout the scenarios is that the technologies that are currently available make up the majority of the optimal remediation strategies. There appears to be very little gain in using technologies that require R&D. The utility functions that were used are primarily responsible for this result. These functions left little room for extensive R&D cost and time. The technologies that are available are able to complete remediation earlier because of the lack of R&D time, and they do it for a lower cost. Even though a new technology may accomplish a process in less time or for less cost, the R&D cost and time overshadow this. Furthermore, containment strategies are generally favorable due to the decrease in cost and time risk caused by the fewer number of processes involved.

The analysis results were affected by some obvious dominance in the data. This can be seen in the data values given in Appendix E. Disposal technology D-1 is obviously dominated by D-2. The respective monitoring technology M-1 is also dominated by M-2. This is due to the extreme values for R&D time and O&M costs involved. The O&M cost for D-1 and M-1 is more than 20 times greater than D-2 and M-2. The retrieval technology R-3 and the treatment technology T-2 are also apparently dominated choices. Their R&D and O&M costs appear to prevent them from being competitive choices, unless due to compatibility issues.

The remaining technology choices make up possible remediation strategies. These strategies were examined using three different analysis scenarios. Most of the

optimal strategies involve currently available technologies; however, many other technologies can provide close results for utility, total time, and total cost. The expected values and distributions for utility, cost, and time were used to compare the strategies. Although actual technologies are used in the analysis, these results should be viewed as notional and dependent on the nature of the data used.

V. Findings and Conclusions

5.1 Conclusions

The goal of this analysis was to produce a generic model to analyze the DOE's selection of technologies for landfill waste site remediation. The following assumptions were used to develop the model:

1) Considered technologies are applicable to the given waste site
2) The decision to stabilize is made by the decision maker
3) Cost and time elements can be modeled using gamma distributions

The model uses the attributes of cost and time to compare possible remediation strategies and technologies. The model incorporates risk into the calculations of these attributes using the probability of technology failure, as well as cost and time penalties for failure. The decision maker's preferences for cost and time are also taken into account using utility functions, which can then be used to determine the optimal strategy for the particular decision maker. Finally, the model can be used to produce the following tools to aid the decision maker.

1) Cumulative and frequency distributions for utility, cost, and time
2) Cost and time plots
3) Rainbow diagrams
4) Tornado diagrams

5.1.1 Recommendations. The analysis of the presented scenarios shows the influence of the utility functions on the result. The range of the cost values for the strategies resulted in cost utilities that were indistinguishable. This caused a loss in the sensitivity for cost and increased the importance of time. Because of this, the relationship between cost and time may inaccurately reflect the decision maker's belief that cost was twice as important as time (k=0.6667). This is not necessarily a problem, provided that the decision maker's utility functions for cost and time are appropriate. These results showed, however, the importance of the target value that was used in the attribute utility functions. Because most of the strategies had costs below the target value, they all had a utility for cost that was similar. This result could change if absolute utility functions for cost and time can be determined, instead of the relative utility functions used for this analysis.

The distributions for cost and time provided the necessary data to compare the alternatives. Some of the technology choices were obviously dominated in terms of cost and time. It may be beneficial to eliminate the technologies that are obviously dominated before determining the attribute utility functions. This could also eliminate the insensitivity that was shown in the cost utility results. In addition, logarithmic transformations of the cost values may eliminate the problems of having a large range of values for the cost attribute.

The cumulative distributions for utility, cost, and time can be used to eliminate those strategies that are clearly dominated. The expected value provides a general

measure, but it neglects the variance and range of the values. Because of this, the distributions for cost and time should be used to compare the strategies with similar results. The variance of the comparable strategies should be analyzed to determine the amount of risk inherent in the cost and time for the strategy.

Plots of the cost and time for the feasible strategies also provide important information to the decision maker. These graphs show the trade-offs that are assumed by the utility functions and shows strategies that should be examined further. Additionally, these two-way plots can show strategies that are obviously dominated or optimal.

Once an optimal strategy is determined, sensitivity analysis can identify how this solution is affected by changes in the values of the variables used. The tornado diagram provides an effective method for displaying these results. Sensitivity analysis helps to determine the variables that have the most influence on the solution. Therefore, emphasis should be placed on the ranges of values assigned to these variables. The rainbow diagram illustrates the effects of changing a particular variable value. Analysis of the scenarios used in this study produced relatively insensitive solutions, which was primarily due to the limited range of alternative technologies.

The data used in the analysis was the best available data for the individual technologies. The model is designed to use output from a LCC model for the cost and time data for each technology. However, the data for this study was gathered from DOE literature, technology principal investigators, and MSE estimates. Because of this, the results and conclusions are presented solely to detail the capabilities of the model. The

results do not reflect the actual characteristics of the given technologies; therefore, the results should be treated as notional.

5.1.2 Contributions to Sponsor. The DA model provides the DOE with a generic analysis tool to compare remediation strategies and technologies. The model provides decision makers with useful information which can be used to make better decisions. Specifically, the DOE requested a generic model to analyze technologies for waste site remediation. The DOE required that the model incorporate LCC and risk information to analyze the technologies. Finally, the DOE required that the model emphasize sensitivity analysis on the solution.

The DA model meets all of the requirements outlined by the DOE. The model is generic in that it allows for new technologies and changes in variable values. Although the model uses three choices for each technology decision, the model can be used to analyze any number of technologies by simply making multiple runs or adding more alternatives to the decision nodes for the technology selections. Additionally, new technologies can be analyzed when they become available. The compatibility constraint allows for relationships between technologies to be maintained. Variables, such as the penalty for technology failure and the process overlaps, allow the user to easily make changes to many of the assumptions in the model.

The DA model is designed to use output from a LCC cost model and risk assessment framework. The life cycle cost model provides simulated cash flows and the cost and process times for the given technology. The technological risk assessment

framework uses information about the technology to develop a probability of failure for the technology. The cost, time, and risk information is then used to calculate the total cost and time for each possible remediation strategy.

Finally, the DA model allows the user to see the effect of changing input values, which can be done using rainbow and tornado diagrams. Sensitivity analysis information is available for any value or uncertainty used in the model. Along with this, the Microsoft Windows© environment makes sensitivity analysis and other functions of the model easy to use and modify.

5.2 Recommendations for Future Research

Throughout the development of the model and the analysis of the data, opportunities for future research were identified. Several ideas, along with a brief description, are provided below.

5.2.1 Technology Data Analysis. Gather output data from a LCC analysis of technologies. This data can then be used to determine the appropriate distributions to use for the cost and time elements in the model. Added to this, the three point approximations used in the model could be analyzed and compared with different discretized distributions.

5.2.2 Modifications to the Utility Functions. The utility functions in this analysis were greatly affected by the technology data involved. When the technologies are changed, different utility functions must be determined. More generic utility

functions may perform better, especially if they are independent of the technologies used in the analysis.

5.2.3 Effectiveness Attributes. Although cost and time are important criteria for technology selection, the effectiveness of technologies is not directly accounted for. In most cases, the model prefers treatment to containment due to the reduced cost and time involved. Attributes could be added to the model to reflect the fact that containment is a temporary strategy. The waste will still have to be treated, but perhaps with a better treatment technology. Other attributes such as safety and environmental impact may be as important as cost and time.

5.3 Summary

The DOE's remediation of waste sites is a complex process that involves significant cost, time, and risk. The selection of technologies is an important decision that requires the allocation of resources. The DA model developed in this study provides an invaluable tool in a time when budgetary, environmental, and public concerns are emphasized.

Decision analysis provides a structured method for analyzing complex problems. The DA model combines several decision analysis techniques to produce useful information for decision makers. The model may not account for all of the details in the process, but by analyzing the important aspects the decision maker can be better informed and make better decisions.

Appendix A: AHP Weight Calculations

Matrix A consists of a_{ij} elements from decision maker's assessments

Weight for objective i : w_i and $a_{ij} = w_i / w_j$

Need vector $\mathbf{w} = [w_1 \ w_2 \ \ldots \ w_n]$

$A\mathbf{w}^T = \Delta\mathbf{w}^T$ is a system of n equations

If decision maker is consistent, then $\Delta = n$. Let Δ_{max} be the largest number for which there is a nontrivial solution to the above equation (w_{max}).

w_{max} can also be approximated by normalizing the columns of matrix A, and averaging the rows. These averages are the approximate weights.

Appendix B: AHP Consistency Index Calculations

1) Compute $A\mathbf{w}^T$

2) Compute $1/n \sum_{i=1}^{i=n} \frac{\text{ith entry in } A\mathbf{w}^T}{\text{ith entry in } \mathbf{w}^T}$

3) The Consistency Index (CI) is computed as follows:

CI = ((#2 result) - n) / (n-1)

4) A Random Index (RI) is used to form a ratio : CI / RI

5) RI values depend on n

6) Generally, if CI / RI < 0.1, then the inconsistency is acceptable

Appendix C: Logarithmic Least Squares Algorithm for HDP

Use A matrix from AHP comparisons

Compute $v_i = \dfrac{(\prod_j a_{ij})^{1/n}}{\sum_i (\prod_j a_{ij})^{1/n}}$ for i, j = 1, 2, ..., n

Compute $z = \min \sum_i \sum_i (\log a_{ij} - \log \dfrac{v_i}{v_j})^2$

Appendix D: DA Model Source Code

The following code is for the DPL© decision analysis software. The code follows the influence diagrams and decision trees given in Chapter 3. This code is for the stabilization model. Therefore, the appropriate utility functions are used. The code begins with the value node assignments from the EXCEL© spreadsheet containing the technology data. The code then assigns the remaining value nodes used in the model. The uncertainty nodes and all calculations follow the value node assignments. Finally, the decision tree structure is coded.

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value Max_Time=10;
value Max_Cost=100000000;
excel(Excel_1,"CA_T1_CAT") value CA_T1_CAT;
excel(Excel_1,"CA_T2_CAT") value CA_T2_CAT;
excel(Excel_1,"CA_T3_CAT") value CA_T3_CAT;
excel(Excel_1,"S_T1_CAT") value S_T1_CAT;
excel(Excel_1,"S_T2_CAT") value S_T2_CAT;
excel(Excel_1,"S_T3_CAT") value S_T3_CAT;
excel(Excel_1,"R_T1_CAT") value R_T1_CAT;
excel(Excel_1,"R_T2_CAT") value R_T2_CAT;
excel(Excel_1,"R_T3_CAT") value R_T3_CAT;
excel(Excel_1,"T_T1_CAT") value T_T1_CAT;
excel(Excel_1,"T_T2_CAT") value T_T2_CAT;
excel(Excel_1,"T_T3_CAT") value T_T3_CAT;
excel(Excel_1,"D_T1_CAT") value D_T1_CAT;
excel(Excel_1,"D_T2_CAT") value D_T2_CAT;
excel(Excel_1,"D_T3_CAT") value D_T3_CAT;
excel(Excel_1,"C_T1_CAT") value C_T1_CAT;
excel(Excel_1,"C_T2_CAT") value C_T2_CAT;
excel(Excel_1,"C_T3_CAT") value C_T3_CAT;
excel(Excel_1,"M_T1_CAT") value M_T1_CAT;
excel(Excel_1,"M_T2_CAT") value M_T2_CAT;
excel(Excel_1,"M_T3_CAT") value M_T3_CAT;
excel(Excel_1,"T1_FACT") value T1_FACT;
excel(Excel_1,"T2_FACT") value T2_FACT;
excel(Excel_1,"T3_FACT") value T3_FACT;
decision Characterization__Assessment.{Tech1,Tech2,Tech3};
decision Stabilize_.{Yes,No};
decision Stabilization.{Tech1,Tech2,Tech3};
decision Treat__Contain_.{Treat,Contain};
decision Removal.{Tech1,Tech2,Tech3};
decision Containment.{Tech1,Tech2,Tech3};
decision Treatment.{Tech1,Tech2,Tech3};
decision Disposal.{Tech1,Tech2,Tech3};
decision Monitor.{Tech1,Tech2,Tech3};
value R_D1_Time_Mean|Characterization__Assessment=
        CA_T1_RDTU,                 // Characterization__Assessment.Tech1
        CA_T2_RDTU,                 // Characterization__Assessment.Tech2
        CA_T3_RDTU;                 // Characterization__Assessment.Tech3
value R_D1_Time_Std_Dev|Characterization__Assessment=
        CA_T1_RDTO,                 // Characterization__Assessment.Tech1
        CA_T2_RDTO,                 // Characterization__Assessment.Tech2
        CA_T3_RDTO;                 // Characterization__Assessment.Tech3
value O_M1_Time_Mean|Characterization__Assessment=
        CA_T1_OMTU,                 // Characterization__Assessment.Tech1
```

```
        CA_T2_OMTU,                  // Characterization__Assessment.Tech2
        CA_T3_OMTU;                  // Characterization__Assessment.Tech3
value O_M1_Time_Std_Dev|Characterization__Assessment=
        CA_T1_OMTO,                  // Characterization__Assessment.Tech1
        CA_T2_OMTO,                  // Characterization__Assessment.Tech2
        CA_T3_OMTO;                  // Characterization__Assessment.Tech3
value R_D1_Fund_Level|Characterization__Assessment=
        CA_T1_RDCU,                  // Characterization__Assessment.Tech1
        CA_T2_RDCU,                  // Characterization__Assessment.Tech2
        CA_T3_RDCU;                  // Characterization__Assessment.Tech3
value O_M1_Cost_Mean|Characterization__Assessment=
        CA_T1_OMCU,                  // Characterization__Assessment.Tech1
        CA_T2_OMCU,                  // Characterization__Assessment.Tech2
        CA_T3_OMCU;                  // Characterization__Assessment.Tech3
value O_M1_Cost_Std_Dev|Characterization__Assessment=
        CA_T1_OMCO,                  // Characterization__Assessment.Tech1
        CA_T2_OMCO,                  // Characterization__Assessment.Tech2
        CA_T3_OMCO;                  // Characterization__Assessment.Tech3
value Prob_Fail1|Characterization__Assessment=
        CA_T1_PROB,                  // Characterization__Assessment.Tech1
        CA_T2_PROB,                  // Characterization__Assessment.Tech2
        CA_T3_PROB;                  // Characterization__Assessment.Tech3
value R_D2_Time_Mean|Stabilization=
        S_T1_RDTU,                   // Stabilization.Tech1
        S_T2_RDTU,                   // Stabilization.Tech2
        S_T3_RDTU;                   // Stabilization.Tech3
value R_D2_Time_Std_Dev|Stabilization=
        S_T1_RDTO,                   // Stabilization.Tech1
        S_T2_RDTO,                   // Stabilization.Tech2
        S_T3_RDTO;                   // Stabilization.Tech3
value O_M2_Time_Mean|Stabilization=
        S_T1_OMTU,                   // Stabilization.Tech1
        S_T2_OMTU,                   // Stabilization.Tech2
        S_T3_OMTU;                   // Stabilization.Tech3
value O_M2_Time_Std_Dev|Stabilization=
        S_T1_OMTO,                   // Stabilization.Tech1
        S_T2_OMTO,                   // Stabilization.Tech2
        S_T3_OMTO;                   // Stabilization.Tech3
value R_D2_Fund_Level|Stabilization=
        S_T1_RDCU,                   // Stabilization.Tech1
        S_T2_RDCU,                   // Stabilization.Tech2
        S_T3_RDCU;                   // Stabilization.Tech3
value O_M2_Cost_Mean|Stabilization=
        S_T1_OMCU,                   // Stabilization.Tech1
        S_T2_OMCU,                   // Stabilization.Tech2
        S_T3_OMCU;                   // Stabilization.Tech3
value O_M2_Cost_Std_Dev|Stabilization=
        S_T1_OMCO,                   // Stabilization.Tech1
        S_T2_OMCO,                   // Stabilization.Tech2
        S_T3_OMCO;                   // Stabilization.Tech3
value Prob_Fail2|Stabilization=
        S_T1_PROB,                   // Stabilization.Tech1
        S_T2_PROB,                   // Stabilization.Tech2
```

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        S_T3_PROB;                  // Stabilization.Tech3
value R_D3_Time_Mean|Removal=
        R_T1_RDTU,                  // Removal.Tech1
        R_T2_RDTU,                  // Removal.Tech2
        R_T3_RDTU;                  // Removal.Tech3
value R_D3_Time_Std_Dev|Removal=
        R_T1_RDTO,                  // Removal.Tech1
        R_T2_RDTO,                  // Removal.Tech2
        R_T3_RDTO;                  // Removal.Tech3
value O_M3_Time_Mean|Removal=
        R_T1_OMTU,                  // Removal.Tech1
        R_T2_OMTU,                  // Removal.Tech2
        R_T3_OMTU;                  // Removal.Tech3
value O_M3_Time_Std_Dev|Removal=
        R_T1_OMTO,                  // Removal.Tech1
        R_T2_OMTO,                  // Removal.Tech2
        R_T3_OMTO;                  // Removal.Tech3
value R_D3_Fund_Level|Removal=
        R_T1_RDCU,                  // Removal.Tech1
        R_T2_RDCU,                  // Removal.Tech2
        R_T3_RDCU;                  // Removal.Tech3
value O_M3_Cost_Mean|Removal=
        R_T1_OMCU,                  // Removal.Tech1
        R_T2_OMCU,                  // Removal.Tech2
        R_T3_OMCU;                  // Removal.Tech3
value O_M3_Cost_Std_Dev|Removal=
        R_T1_OMCO,                  // Removal.Tech1
        R_T2_OMCO,                  // Removal.Tech2
        R_T3_OMCO;                  // Removal.Tech3
value Prob_Fail3|Removal=
        R_T1_PROB,                  // Removal.Tech1
        R_T2_PROB,                  // Removal.Tech2
        R_T3_PROB;                  // Removal.Tech3
value R_D4_Time_Mean|Treatment=
        T_T1_RDTU,                  // Treatment.Tech1
        T_T2_RDTU,                  // Treatment.Tech2
        T_T3_RDTU;                  // Treatment.Tech3
value R_D4_Time_Std_Dev|Treatment=
        T_T1_RDTO,                  // Treatment.Tech1
        T_T2_RDTO,                  // Treatment.Tech2
        T_T3_RDTO;                  // Treatment.Tech3
value O_M4_Time_Mean|Treatment=
        T_T1_OMTU,                  // Treatment.Tech1
        T_T2_OMTU,                  // Treatment.Tech2
        T_T3_OMTU;                  // Treatment.Tech3
value O_M4_Time_Std_Dev|Treatment=
        T_T1_OMTO,                  // Treatment.Tech1
        T_T2_OMTO,                  // Treatment.Tech2
        T_T3_OMTO;                  // Treatment.Tech3
value R_D4_Fund_Level|Treatment=
        T_T1_RDCU,                  // Treatment.Tech1
        T_T2_RDCU,                  // Treatment.Tech2
        T_T3_RDCU;                  // Treatment.Tech3
```

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value O_M4_Cost_Mean|Treatment=
        T_T1_OMCU,              // Treatment.Tech1
        T_T2_OMCU,              // Treatment.Tech2
        T_T3_OMCU;              // Treatment.Tech3
value O_M4_Cost_Std_Dev|Treatment=
        T_T1_OMCO,              // Treatment.Tech1
        T_T2_OMCO,              // Treatment.Tech2
        T_T3_OMCO;              // Treatment.Tech3
value Prob_Fail4|Treatment=
        T_T1_PROB,              // Treatment.Tech1
        T_T2_PROB,              // Treatment.Tech2
        T_T3_PROB;              // Treatment.Tech3
value R_D5_Time_Mean|Disposal=
        D_T1_RDTU,              // Disposal.Tech1
        D_T2_RDTU,              // Disposal.Tech2
        D_T3_RDTU;              // Disposal.Tech3
value R_D5_Time_Std_Dev|Disposal=
        D_T1_RDTO,              // Disposal.Tech1
        D_T2_RDTO,              // Disposal.Tech2
        D_T3_RDTO;              // Disposal.Tech3
value O_M5_Time_Mean|Disposal=
        D_T1_OMTU,              // Disposal.Tech1
        D_T2_OMTU,              // Disposal.Tech2
        D_T3_OMTU;              // Disposal.Tech3
value O_M5_Time_Std_Dev|Disposal=
        D_T1_OMTO,              // Disposal.Tech1
        D_T2_OMTO,              // Disposal.Tech2
        D_T3_OMTO;              // Disposal.Tech3
value R_D5_Fund_Level|Disposal=
        D_T1_RDCU,              // Disposal.Tech1
        D_T2_RDCU,              // Disposal.Tech2
        D_T3_RDCU;              // Disposal.Tech3
value O_M5_Cost_Mean|Disposal=
        D_T1_OMCU,              // Disposal.Tech1
        D_T2_OMCU,              // Disposal.Tech2
        D_T3_OMCU;              // Disposal.Tech3
value O_M5_Cost_Std_Dev|Disposal=
        D_T1_OMCO,              // Disposal.Tech1
        D_T2_OMCO,              // Disposal.Tech2
        D_T3_OMCO;              // Disposal.Tech3
value Prob_Fail5|Disposal=
        D_T1_PROB,              // Disposal.Tech1
        D_T2_PROB,              // Disposal.Tech2
        D_T3_PROB;              // Disposal.Tech3
value R_D6_Time_Mean|Containment=
        C_T1_RDTU,              // Containment.Tech1
        C_T2_RDTU,              // Containment.Tech2
        C_T3_RDTU;              // Containment.Tech3
value R_D6_Time_Std_Dev|Containment=
        C_T1_RDTO,              // Containment.Tech1
        C_T2_RDTO,              // Containment.Tech2
        C_T3_RDTO;              // Containment.Tech3
value O_M6_Time_Mean|Containment=
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        C_T1_OMTU,                      // Containment.Tech1
        C_T2_OMTU,                      // Containment.Tech2
        C_T3_OMTU;                      // Containment.Tech3
value O_M6_Time_Std_Dev|Containment=
        C_T1_OMTO,                      // Containment.Tech1
        C_T2_OMTO,                      // Containment.Tech2
        C_T3_OMTO;                      // Containment.Tech3
value R_D6_Fund_Level|Containment=
        C_T1_RDCU,                      // Containment.Tech1
        C_T2_RDCU,                      // Containment.Tech2
        C_T3_RDCU;                      // Containment.Tech3
value O_M6_Cost_Mean|Containment=
        C_T1_OMCU,                      // Containment.Tech1
        C_T2_OMCU,                      // Containment.Tech2
        C_T3_OMCU;                      // Containment.Tech3
value O_M6_Cost_Std_Dev|Containment=
        C_T1_OMCO,                      // Containment.Tech1
        C_T2_OMCO,                      // Containment.Tech2
        C_T3_OMCO;                      // Containment.Tech3
value Prob_Fail6|Containment=
        C_T1_PROB,                      // Containment.Tech1
        C_T2_PROB,                      // Containment.Tech2
        C_T3_PROB;                      // Containment.Tech3
value R_D7_Time_Mean|Monitor=
        M_T1_RDTU,                      // Monitor.Tech1
        M_T2_RDTU,                      // Monitor.Tech2
        M_T3_RDTU;                      // Monitor.Tech3
value R_D7_Time_Std_Dev|Monitor=
        M_T1_RDTO,                      // Monitor.Tech1
        M_T2_RDTO,                      // Monitor.Tech2
        M_T3_RDTO;                      // Monitor.Tech3
value O_M7_Time_Mean|Monitor=
        M_T1_OMTU,                      // Monitor.Tech1
        M_T2_OMTU,                      // Monitor.Tech2
        M_T3_OMTU;                      // Monitor.Tech3
value O_M7_Time_Std_Dev|Monitor=
        M_T1_OMTO,                      // Monitor.Tech1
        M_T2_OMTO,                      // Monitor.Tech2
        M_T3_OMTO;                      // Monitor.Tech3
value R_D7_Fund_Level|Monitor=
        M_T1_RDCU,                      // Monitor.Tech1
        M_T2_RDCU,                      // Monitor.Tech2
        M_T3_RDCU;                      // Monitor.Tech3
value O_M7_Cost_Mean|Monitor=
        M_T1_OMCU,                      // Monitor.Tech1
        M_T2_OMCU,                      // Monitor.Tech2
        M_T3_OMCU;                      // Monitor.Tech3
value O_M7_Cost_Std_Dev|Monitor=
        M_T1_OMCO,                      // Monitor.Tech1
        M_T2_OMCO,                      // Monitor.Tech2
        M_T3_OMCO;                      // Monitor.Tech3
value Prob_Fail7|Monitor=
        M_T1_PROB,                      // Monitor.Tech1
```

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        M_T2_PROB,                  // Monitor.Tech2
        M_T3_PROB;                  // Monitor.Tech3
value Cat1|Characterization__Assessment=
        CA_T1_CAT,                  // Characterization__Assessment.Tech1
        CA_T2_CAT,                  // Characterization__Assessment.Tech2
        CA_T3_CAT;                  // Characterization__Assessment.Tech3
value Cat2|Stabilization=
        S_T1_CAT,                   // Stabilization.Tech1
        S_T2_CAT,                   // Stabilization.Tech2
        S_T3_CAT;                   // Stabilization.Tech3
value Cat6|Containment=
        C_T1_CAT,                   // Containment.Tech1
        C_T2_CAT,                   // Containment.Tech2
        C_T3_CAT;                   // Containment.Tech3
value Cat3|Removal=
        R_T1_CAT,                   // Removal.Tech1
        R_T2_CAT,                   // Removal.Tech2
        R_T3_CAT;                   // Removal.Tech3
value Cat4|Treatment=
        T_T1_CAT,                   // Treatment.Tech1
        T_T2_CAT,                   // Treatment.Tech2
        T_T3_CAT;                   // Treatment.Tech3
value Cat5|Disposal=
        D_T1_CAT,                   // Disposal.Tech1
        D_T2_CAT,                   // Disposal.Tech2
        D_T3_CAT;                   // Disposal.Tech3
value Cat7|Monitor=
        M_T1_CAT,                   // Monitor.Tech1
        M_T2_CAT,                   // Monitor.Tech2
        M_T3_CAT;                   // Monitor.Tech3
value Disposal_Factor|Treatment=
        T1_FACT,                        // Treatment.Tech1
        T2_FACT,                        // Treatment.Tech2
        T3_FACT;                        // Treatment.Tech3
chance R_D_T1.{Short,Normal,Long}=gamma(R_D1_Time_Mean,R_D1_Time_Std_Dev);
chance O_M_T1.{Short,Normal,Long}=gamma(O_M1_Time_Mean,O_M1_Time_Std_Dev);
chance O_M_C1.{Low,Normal,High}=gamma(O_M1_Cost_Mean,O_M1_Cost_Std_Dev);
chance R_D_T2.{Short,Normal,Long}=gamma(R_D2_Time_Mean,R_D2_Time_Std_Dev);
chance O_M_T2.{Short,Normal,Long}=gamma(O_M2_Time_Mean,O_M2_Time_Std_Dev);
chance O_M_C2.{Low,Normal,High}=gamma(O_M2_Cost_Mean,O_M2_Cost_Std_Dev);
chance R_D_T3.{Short,Normal,Long}=gamma(R_D3_Time_Mean,R_D3_Time_Std_Dev);
chance O_M_T3.{Short,Normal,Long}=gamma(O_M3_Time_Mean,O_M3_Time_Std_Dev);
chance O_M_C3.{Low,Normal,High}=gamma(O_M3_Cost_Mean,O_M3_Cost_Std_Dev);
chance R_D_T4.{Short,Normal,Long}=gamma(R_D4_Time_Mean,R_D4_Time_Std_Dev);
chance O_M_T4.{Short,Normal,Long}=gamma(O_M4_Time_Mean,O_M4_Time_Std_Dev);
chance O_M_C4.{Low,Normal,High}=gamma(O_M4_Cost_Mean,O_M4_Cost_Std_Dev);
chance R_D_T5.{Short,Normal,Long}=gamma(R_D5_Time_Mean,R_D5_Time_Std_Dev);
chance O_M_T5.{Short,Normal,Long}=gamma(O_M5_Time_Mean,O_M5_Time_Std_Dev);
chance O_M_C5.{Low,Normal,High}=gamma(O_M5_Cost_Mean,O_M5_Cost_Std_Dev);
chance R_D_T6.{Short,Normal,Long}=gamma(R_D6_Time_Mean,R_D6_Time_Std_Dev);
chance O_M_T6.{Short,Normal,Long}=gamma(O_M6_Time_Mean,O_M6_Time_Std_Dev);
chance O_M_C6.{Low,Normal,High}=gamma(O_M6_Cost_Mean,O_M6_Cost_Std_Dev);
chance R_D_T7.{Short,Normal,Long}=gamma(R_D7_Time_Mean,R_D7_Time_Std_Dev);
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chance O_M_T7.{Short,Normal,Long}=gamma(O_M7_Time_Mean,O_M7_Time_Std_Dev);
chance O_M_C7.{Low,Normal,High}=gamma(O_M7_Cost_Mean,O_M7_Cost_Std_Dev);
value R_D_C1=@pv(R_D1_Fund_Level,Rate-Inflation,@if(R_D1_Time_Mean == 0.000001,0,R_D_T1));
value Time1=@if(R_D1_Time_Mean == 0.000001,0,R_D_T1)+O_M_T1*(1-Overlap1);
value R_D_C2=@pv(R_D2_Fund_Level,Rate-Inflation,@if(R_D2_Time_Mean == 0.000001,0,R_D_T2));
value R_D_C3=@pv(R_D3_Fund_Level,Rate-Inflation,@if(R_D3_Time_Mean == 0.000001,0,R_D_T3));
value R_D_C4=@pv(R_D4_Fund_Level,Rate-Inflation,@if(R_D4_Time_Mean == 0.000001,0,R_D_T4));
value R_D_C5=@pv(R_D5_Fund_Level,Rate-Inflation,@if(R_D5_Time_Mean == 0.000001,0,R_D_T5));
value R_D_C6=@pv(R_D6_Fund_Level,Rate-Inflation,@if(R_D6_Time_Mean == 0.000001,0,R_D_T6));
value R_D_C7=@pv(R_D7_Fund_Level,Rate-Inflation,@if(R_D7_Time_Mean == 0.000001,0,R_D_T7));
value Cost1=R_D_C1+(O_M_C1*(pow(1+Inflation,R_D_T1))*(pow(1+Rate,-R_D_T1)));
value Fail_Cost1=(R_D_C1+Stop_Time1*(Cost1-R_D_C1)+Fix_Cost1*(pow(1+Inflation,(Time1-(1-
Stop_Time1)*(O_M_T1)))*(pow(1+Rate,-(Time1-(1-Stop_Time1)*(O_M_T1))))));
value Fail_Time1=(Time1+(Stop_Time1-(1-Overlap1))*(O_M_T1)+Fix_Time1);
chance Total_Cost1.{Fail,Success}={Prob_Fail1},
=
        Fail_Cost1,                    // Total_Cost1.Fail
        Cost1;                         // Total_Cost1.Success
chance Total_Time1.{Fail,Success}={Prob_Fail1},
=
        Fail_Time1,                    // Total_Time1.Fail
        Time1;                         // Total_Time1.Success
value Time2=@max((@if(R_D_T2>Total_Time1,R_D_T2,Total_Time1))+(1-
Overlap2)*O_M_T2,Total_Time1+Overlap1*O_M_T1);
value Cost2=R_D_C2+(O_M_C2*(pow(1+Inflation,@max(R_D_T2,Total_Time1)))*(pow(1+Rate,-
(@max(R_D_T2,Total_Time1)))));
value Fail_Time2=(Time2+(Stop_Time2-(1-Overlap2))*(O_M_T2)+Fix_Time2);
value Fail_Cost2=(R_D_C2+Stop_Time2*(Cost2-R_D_C2)+Fix_Cost2*(pow(1+Inflation,(Time2-(1-
Stop_Time2)*(O_M_T2)))*(pow(1+Rate,-(Time2-(1-Stop_Time2)*(O_M_T2))))));
chance Total_Time2.{Fail,Success}={Prob_Fail2},
=
        Fail_Time2,                    // Total_Time2.Fail
        Time2;                         // Total_Time2.Success
chance Total_Cost2.{Fail,Success}={Prob_Fail2},
=
        Fail_Cost2,                    // Total_Cost2.Fail
        Cost2;                         // Total_Cost2.Success
value Which_Time|Stabilize_=
        Total_Time2,           // Stabilize_.Yes
        Total_Time1;           // Stabilize_.No
value Which_O_M|Stabilize_=
        Total_Time2+Overlap2*O_M_T2, // Stabilize_.Yes
        Total_Time1+Overlap1*O_M_T1; // Stabilize_.No
value Time3=@max((@if(R_D_T3>Which_Time,R_D_T3,Which_Time))+(1-Overlap3)*O_M_T3,
Which_O_M);
value Time6=@max((@if(R_D_T6>Which_Time,R_D_T6,Which_Time))+(1-Overlap6)*O_M_T6,
Which_O_M);
value Cost3=R_D_C3+(O_M_C3*(pow(1+Inflation,@max(R_D_T3,Which_Time)))*(pow(1+Rate,-
(@max(R_D_T3,Which_Time)))));
value Cost6=R_D_C6+(O_M_C6*(pow(1+Inflation,@max(R_D_T6,Which_Time)))*(pow(1+Rate,-
(@max(R_D_T6,Which_Time)))));
value Fail_Time6=(Time6+(Stop_Time6-(1-Overlap6))*(O_M_T6)+Fix_Time6);
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value Fail_Cost6=(R_D_C6+Stop_Time6*(Cost6-R_D_C6)+Fix_Cost6*(pow(1+Inflation,(Time6-(1-
Stop_Time6)*(O_M_T6)))*(pow(1+Rate,-(Time6-(1-Stop_Time6)*(O_M_T6))))));
value Fail_Time3=(Time3+(Stop_Time3-(1-Overlap3))*(O_M_T3)+Fix_Time3);
value Fail_Cost3=(R_D_C3+Stop_Time3*(Cost3-R_D_C3)+Fix_Cost3*(pow(1+Inflation,(Time3-(1-
Stop_Time3)*(O_M_T3)))*(pow(1+Rate,-(Time3-(1-Stop_Time3)*(O_M_T3))))));
chance Total_Cost3.{Fail,Success}={Prob_Fail3},
=
        Fail_Cost3,                     // Total_Cost3.Fail
        Cost3;                          // Total_Cost3.Success
chance Total_Time3.{Fail,Success}={Prob_Fail3},
=
        Fail_Time3,                     // Total_Time3.Fail
        Time3;                          // Total_Time3.Success
chance Total_Time6.{Fail,Success}={Prob_Fail6},
=
        Fail_Time6,                     // Total_Time6.Fail
        Time6;                          // Total_Time6.Success
chance Total_Cost6.{Fail,Success}={Prob_Fail6},
=
        Fail_Cost6,                     // Total_Cost6.Fail
        Cost6;                          // Total_Cost6.Success
value Time4=@max((@if(R_D_T4>Time3,R_D_T4,Time3))+(1-Overlap4)*O_M_T4,
Total_Time3+Overlap3*O_M_T3);
value Cost4=R_D_C4+(O_M_C4*(pow(1+Inflation,@max(R_D_T4,Time3)))*(pow(1+Rate,-
(@max(R_D_T4,Time3)))));
value Fail_Time4=(Time4+(Stop_Time4-(1-Overlap4))*(O_M_T4)+Fix_Time4);
value Fail_Cost4=(R_D_C4+Stop_Time4*(Cost4-R_D_C4)+Fix_Cost4*(pow(1+Inflation,(Time4-(1-
Stop_Time4)*(O_M_T4)))*(pow(1+Rate,-(Time4-(1-Stop_Time4)*(O_M_T4))))));
chance Total_Time4.{Fial,Success}={Prob_Fail4},
=
        Fail_Time4,                     // Total_Time4.Fial
        Time4;                          // Total_Time4.Success
chance Total_Cost4.{Fail,Success}={Prob_Fail4},
=
        Fail_Cost4,                     // Total_Cost4.Fail
        Cost4;                          // Total_Cost4.Success
value Time5=@max((@if(R_D_T5>Time4,R_D_T5,Time4))+(1-Overlap5)*Disposal_Factor*O_M_T5,
Total_Time4+Overlap4*O_M_T4);
value
Cost5=R_D_C5+(Disposal_Factor*O_M_C5*(pow(1+Inflation,@max(R_D_T5,Time4)))*(pow(1+Rate,-
(@max(R_D_T5,Time4)))));
value Fail_Time5=(Time5+(Stop_Time5-(1-Overlap5))*(Disposal_Factor*O_M_T5)+Fix_Time5);
value Fail_Cost5=(R_D_C5+Stop_Time5*(Cost5-R_D_C5)+Fix_Cost5*(pow(1+Inflation,(Time5-(1-
Stop_Time5)*(Disposal_Factor*O_M_T5)))*(pow(1+Rate,-(Time5-(1-
Stop_Time5)*(Disposal_Factor*O_M_T5))))));
chance Total_Time5.{Fail,Success}={Prob_Fail5},
=
        Fail_Time5,                     // Total_Time5.Fail
        Time5;                          // Total_Time5.Success
chance Total_Cost5.{Fail,Success}={Prob_Fail5},
=
        Fail_Cost5,                     // Total_Cost5.Fail
        Cost5;                          // Total_Cost5.Success
```

```
value TC_Time|Treat__Contain_=
        Total_Time5,            // Treat__Contain_.Treat
        Total_Time6;            // Treat__Contain_.Contain
value TC_O_M|Treat__Contain_=
        Total_Time5+Overlap5*O_M_T5, // Treat__Contain_.Treat
        Total_Time6+Overlap6*O_M_T6; // Treat__Contain_.Contain
value Time7=@max((@if(R_D_T7>TC_Time,R_D_T7,TC_Time))+O_M_T7,TC_O_M);
value Cost7=R_D_C7+(O_M_C7*(pow(1+Inflation,@max(R_D_T7,TC_Time)))*(pow(1+Rate,-
(@max(R_D_T7,TC_Time)))));
value Fail_Time7=(Time7-(1-Stop_Time7)*(O_M_T7)+Fix_Time7);
value Fail_Cost7=(R_D_C7+Stop_Time7*(Cost7-R_D_C7)+Fix_Cost7*(pow(1+Inflation,(Time7-(1-
Stop_Time7)*(O_M_T7 )))*(pow(1+Rate,-(Time7-(1-Stop_Time7)*(O_M_T7))))));
chance Total_Time7.{Fail,Success}={Prob_Fail7},
=
        Fail_Time7,                     // Total_Time7.Fail
        Time7;                          // Total_Time7.Success
chance Total_Cost7.{Fail,Success}={Prob_Fail7},
=
        Fail_Cost7,                     // Total_Cost7.Fail
        Cost7;                          // Total_Cost7.Success

sequence( attributes = 8,
        objective = xland($1<=Max_Cost, $2<=Max_Time) ? k*(@if($1<=77000000,1.001-
0.0001273*exp(0.00000009852*$1),-0.000002347+121*exp(-0.00000006601*$1))) + (1-
k)*(@if($2<=7.7,1-0.0001245*exp(0.9879*$2),-0.000000000002095+121*exp(-0.6601*$2))) : 0,
        constraint = xland(@if($3 > 0, xlor($4 == $3, $5 == $3), @if($3 < 0, xland($4 != $3, $5 != $3),
1)), @if($4 > 0, xlor($3 == $4, $5 == $4, $6 == $4), @if($4 < 0, xland($3 != $4, $5 != $4, $6 != $4), 1)),
@if($5 > 0, xlor($3 == $5, $4 == $5, $6 == $5, $7 == $5), @if($5 < 0, xland($3 != $5, $4 != $5, $6 != $5,
$7 != $5), 1)), @if($6 > 0, xlor($4 == $6, $5 == $6, $7 == $6, $8 == $6), @if($6 < 0, xland($4 != $6, $5
!= $6, $7 != $6, $8 != $6), 1)), @if($7 > 0, xlor($5 == $7, $6 == $7, $8 == $7), @if($7 < 0, xland($5 !=
$7, $6 != $7, $8 != $7), 1)), @if($8 > 0, xlor($6 == $8, $7 == $8), @if($8 < 0, xland($6 != $8, $7 != $8),
1))) ? 0 : halt(-9999999) ):
decide to Characterization__Assessment then
set Stabilize_.Yes then
decide to Stabilization then decide
        to Treat__Contain_.Treat then
                decide to Removal then
                decide to Treatment then
                decide to Disposal then
                decide to Monitor and get 0,0,Cat1,Cat2,Cat3,Cat4,Cat5,Cat7 then
                gamble on R_D_T1 then
                gamble on O_M_T1 then
                gamble on O_M_C1 then
                gamble on Total_Time1 then
                gamble on Total_Cost1 and get Total_Cost1,0,0,0,0,0,0,0 then
                gamble on R_D_T2 then
                gamble on O_M_T2 then
                gamble on O_M_C2 then
                gamble on Total_Time2 then
                gamble on Total_Cost2 and get Total_Cost2,0,0,0,0,0,0,0 then
                gamble on R_D_T3 then
                gamble on O_M_T3 then
                gamble on O_M_C3 then
```

```
          gamble on Total_Time3 then
          gamble on Total_Cost3 and get Total_Cost3,0,0,0,0,0,0,0 then
          gamble on R_D_T4 then
          gamble on O_M_T4 then
          gamble on O_M_C4 then
          gamble on Total_Time4 then
          gamble on Total_Cost4 and get Total_Cost4,0,0,0,0,0,0,0 then
          gamble on R_D_T5 then
          gamble on O_M_T5 then
          gamble on O_M_C5 then
          gamble on Total_Time5 then
          gamble on Total_Cost5 and get Total_Cost5,0,0,0,0,0,0,0 then
          gamble on R_D_T7 then
          gamble on O_M_T7 then
          gamble on O_M_C7 then
          gamble on Total_Time7 then
          gamble on Total_Cost7 and get Total_Cost7,Total_Time7,0,0,0,0,0,0
to Treat__Contain_.Contain then
          decide to Containment then
          decide to Monitor and get 0,0,Cat1,Cat2,Cat6,Cat7,0,0 then
          gamble on R_D_T1 then
          gamble on O_M_T1 then
          gamble on O_M_C1 then
          gamble on Total_Time1 then
          gamble on Total_Cost1 and get Total_Cost1,0,0,0,0,0,0,0 then
          gamble on R_D_T2 then
          gamble on O_M_T2 then
          gamble on O_M_C2 then
          gamble on Total_Time2 then
          gamble on Total_Cost2 and get Total_Cost2,0,0,0,0,0,0,0 then
          gamble on R_D_T6 then
          gamble on O_M_T6 then
          gamble on O_M_C6 then
          gamble on Total_Time6 then
          gamble on Total_Cost6 and get Total_Cost6,0,0,0,0,0,0,0 then
          gamble on R_D_T7 then
          gamble on O_M_T7 then
          gamble on O_M_C7 then
          gamble on Total_Time7 then
          gamble on Total_Cost7 and get Total_Cost7,Total_Time7,0,0,0,0,0,0
```

Appendix E: Variable Descriptions and Calculations

The variables used in each process model are described below. Each process model uses all of the variables listed, with the exception of the Overlap variable. This variable is not used in the monitoring process because monitoring is the final process. The character **I** represents a process, so that:

I = (1: Characterization, 2: Stabilization, 3: Retrieval, 4: Treatment, 5: Disposal, 6: Containment, 7: Monitoring)

For calculations, (**I**-1) represents the process that precedes process **I**.

Name: R&D**I**_Fund_Level

Description:

Amount of money allocated each year for R&D for the selected technology. This value is constant and represents the funding level each year beginning at year 0.

Name: R&D**I**_Time (mean and standard deviation)

Description:

Number of years for R&D funding for the selected technology. The mean and standard deviation are used for the parameters for the distribution of R&D Time.

Name: O&M**I**_Cost (mean and standard deviation)

Description:

The present value of the cost of the selected technology from the end of R&D until process **I** completion. These values are output from the LCC model. The mean and standard deviation are used for the parameters for the distribution of O&M Cost.

Name: O&M**I**_Time (mean and standard deviation)

Description:

The time required for the selected technology to complete process **I**, from the end of R&D. The mean and standard deviation are used for the parameters for the distribution of O&M Time.

Name: Prob_Fail**I**

Description:

The probability that the selected technology fails during process **I**, given that the technology was successfully developed.

Name: Cat**I**

Description:

The category of the selected technology for process **I**. This value is used in the compatibility constraint for the technology strategy.

Name: Disposal_Factor

Description:

This variable is used only in the treatment process model. It represents the ratio of the volume of the waste after treatment to the volume of the waste before treatment. This value is then used to adjust the O&M_Cost and O&M_Time for disposal, to reflect the change in volume.

Name: Overlap**I**

Description:

The percentage of process **I** O&M time that is overlapped by the succeeding process. (1-Overlap**I**) represents the amount of O&M for process **I** that is complete

before the succeeding process begins. For example, Overlap3 = 0.9 implies that treatment begins when 10% of removal is complete.

Name: Stop_Time**I**

Description:

The percentage of O&M time in process **I** when technology failure will occur. For example, Stop_Time3 = 0.3, then if the removal technology fails, it will be considered a failure after 30% removal O&M time has passed.

Name: Fix_Time**I**

Description:

The penalty time required to complete process **I** if technology failure occurs

Name: Fix_Cost**I**

Description:

The penalty cost required to complete process **I** if technology failure occurs.

Name: R&D_T**I**

Description:

The output value from the R&D time distribution. This value represents the number of years for R&D for the selected technology.

Name: O&M_T**I**

Description:

The output value from the O&M time distribution. This value represents the number of years for O&M for the selected technology to perform process **I**.

Name: Rate

Description:

This value represents the rate of return on investments. The nominal value used is 7%, unless otherwise stated.

Name: Inflation

Description:

This value represents the inflation rate. The nominal value used is 2%, unless otherwise stated.

Name: O&M_C**I**

Description:

The output value from the O&M cost distribution. This value represents the present value of O&M cost for the selected technology to perform process **I**.

Name: R&D_C**I**

Description:

The total present value of R&D cost for the selected technology, given the annual funding level and number of years for R&D. This value is calculated using a preset value of an annuity formula.

$$\mathrm{R\&D\_Cost}\mathbf{I} = \mathrm{R\&D\_Funding\_Level} \cdot \frac{(1+\mathrm{Rate}-\mathrm{Inflation})^{\mathrm{R\&D\_Time}\mathbf{I}}-1}{(\mathrm{Rate}-\mathrm{Inflation})\cdot(1+\mathrm{Rate}-\mathrm{Inflation})^{\mathrm{R\&D\_Time}\mathbf{I}}}$$

Name: Time**I**

Description:

The total time required from the beginning of remediation through process **I**. This value also represents the time that the succeeding process can begin O&M, if the technology for process **I** does not fail. Thus, Time7 is the total time for the technology portfolio to perform all processes, if the monitoring process does not fail. The calculation involves checks to ensure that R&D is complete, and that non-consecutive processes do not overlap.

$$\text{Time}\mathbf{I} = \max\begin{bmatrix} \max(\text{R\&D\_Time}\mathbf{I},\ \text{Time}(\mathbf{I}-1)) + (1-\text{Overlap}\mathbf{I})\cdot(\text{O\&M\_Time}\mathbf{I}), \\ \text{Total\_Time}(\mathbf{I}-1) + \text{Overlap}(\mathbf{I}-1)\cdot(\text{O\&M\_Time}(\mathbf{I}-1) \end{bmatrix}$$

Name: Fail_Time**I**

Description:

The total time required from the beginning of remediation through process **I**. This value also represents the time that the succeeding process can begin O&M. This value assumes that the technology for process **I** fails, and is therefore adjusted to reflect the increase. Using the Stop_Time**I** value, a portion of the O&M time for the failed technology is used plus a penalty time value from Fix_Time**I**.

$$\text{Fail\_Time}\mathbf{I} = (\text{Time}\mathbf{I} + (\text{Stop\_Time}\mathbf{I} - (1-\text{Overlap}\mathbf{I}))\cdot\text{O\&M\_Time}\mathbf{I} + \text{Fix\_Time}\mathbf{I})$$

Name: Total_Time**I**

Description:

This uncertain event passes the time value for process **I**. If the technology fails then the Fail_Time**I** value is used. If the technology does not fail, then the value for Time**I** is used.

Name: Cost**I**

Description:

The present value of the total cost for the technology to complete process **I** including all R&D costs, assuming the technology does not fail. This cost is adjusted for inflation and the cost of capital, based on when O&M occurs - from the previous time calculations.

$$\text{Cost}\,\mathbf{I} = \text{R\&D\_Cost}\,\mathbf{I} + \frac{\text{O\&M\_Cost}\,\mathbf{I} \cdot (1 + \text{Inflation})^{\max(\text{R\&D\_Time}\,\mathbf{I},\ \text{Time}\,(\mathbf{I}\text{-}1))}}{(1 + \text{Rate})^{\max(\text{R\&D\_Time}\,\mathbf{I},\ \text{Time}\,(\mathbf{I}\text{-}1))}}$$

Name: Fail_Cost**I**

Description:

The present value of the cost to complete process **I**, if the technology fails. This value includes the R&D cost for the failed technology plus a portion of the O&M cost. A penalty cost is also added from the Fix_Cost**I** value.

$$\text{Fail\_Cost}\mathbf{I} = \text{R\&D\_Cost}\mathbf{I} + \text{Stop\_Time}\mathbf{I} \cdot (\text{Cost}\mathbf{I} - \text{R\&D\_Cost}\mathbf{I}) + \text{Fix\_Cost}\mathbf{I} \cdot \frac{(1+\text{Inflation})^{(\text{Time}\mathbf{I} - (1\text{-Stop\_Time}\mathbf{I}) \cdot \text{O\&M\_Time}\mathbf{I})}}{(1+\text{Rate})^{(\text{Time}\mathbf{I} - (1\text{-Stop\_Time}\mathbf{I}) \cdot \text{O\&M\_Time}\mathbf{I})}}$$

Name: Total_Cost**I**

Description:

This uncertain event passes the cost value for process**I**. If the technology fails, then the value for FailCost**I** is used. If the technology does not fail, then the value for Cost**I** is used.

Appendix F: Technology Compatibility Constraint Description

When the technologies are input into the spreadsheet, it is likely that relationships exist between technologies in different processes. For example, a specific treatment technology might require the use of a specific removal technology. This required coupling can be two-way or one-way. In other words, a two-way coupling may exist where the removal technology also requires the specific treatment technology. Other constraints may include incompatibilities, where one treatment technology cannot be used with a specific removal technology.

A category system is set up in the spreadsheet in order to account for these compatibility constraints. The system uses integers to categorize technologies. When technology data is entered in the spreadsheet, the technologies must also be given categories. A technology is assigned a category of 0 if it is compatible with all other technologies. If a two-way couple is required, then the two technologies should be given a category of some positive integer. For instance, the coupled removal and treatment technologies will have a category of 1. Therefore, when the DA model creates the technology portfolios it will check to see that if a portfolio has one category of 1, then another category should also be assigned 1. If this does not hold, then the portfolio is no longer considered and no calculations are made for that portfolio.

If a two-way incompatibility exists, then the two technologies should be given a category of some negative integer. In this case, if the DA model finds a portfolio with a negative integer for a category, then it will check to ensure that no other category is

assigned that same negative integer. If the portfolio has two categories with the same negative integer, then an incompatibility exists and the portfolio is no longer considered.

This system can account for one-way relationships also. The one-way relationship pertains only to couples, because incompatibility is not a one-way relationship. A one-way couple implies for example, that if a certain removal technology is used then it must be used with a specific treatment technology, however the treatment technology may be used with other removal technologies. To account for this, the incompatibility relationship is used. If a removal technology requires a specific treatment (one-way), then the removal technology and the other treatment technologies are assigned a negative integer category. The examples that follow demonstrate the category system.

	Removal	Treatment
Tech 1	1	0
Tech 2	0	1
Tech 3	0	0

Removal Tech1 and Treatment Tech 2 have to be used together.

	Removal	Treatment
Tech 1	-2	0
Tech 2	0	-2
Tech 3	0	0

Removal Tech1 and Treatment Tech 2 cannot be used together.

	Removal	Treatment
Tech 1	-1	-1
Tech 2	0	0
Tech 3	0	-1

Removal Tech1 must be used with Treatment Tech2

Appendix G: Gamma Function Maximum Likelihood Estimator

In order to determine the parameters for the gamma distribution, the maximum likelihhod estimator (MLE) equations must be satisified. These equations are iterative and must be solved simultaneously.

The following two equations must be satisified [Law and Kelton, 1991: 332]:

$$\ln(\hat{\beta}) + \Psi(\hat{\alpha}) = \frac{\sum_{i=1}^{n} \ln(X_i)}{n} \qquad \hat{\alpha}\hat{\beta} = \overline{X}(n)$$

Note, $\Psi(\hat{\alpha}) = \dfrac{\Gamma'(\hat{\alpha})}{\Gamma(\hat{\alpha})}$ is called the digamma function where Γ' is the derivative of Γ, $\Gamma(z) = \int_0^\infty t^{z-1} e^{-t}\,dt$ for any real number $z > 0$, and

$$\Gamma'(z) = \frac{d \int_0^\infty t^{z-1} e^{-t}\,dt}{dz}$$

Appendix H: Explanation of Distributed Sampling Simulation

The DA model uses simulation of the different cost and time distributions to determine an optimal decision policy. The method of simulation is called distributed sampling, and is described in the DPL© user's manual [ADA, 1995: 427-435]. This approach is an extension of Monte Carlo simulation. Monte Carlo simulation determines the path for a particular iteration using random numbers to select the branch for each uncertainty node. This process is repeated until the number of iterations is reached. The major drawback of this method is that some branches may never be selected, due to the nature of random number generation.

An improvement on this is Modified Monte Carlo simulation. This method distributes the number of iteration samples over the branches for each node. The number of samples assigned to each branch is equal to the number of initial samples times the probability associated with each branch for the node. This technique is called stratified sampling. When the samples are distributed, then the simulation begins.

Distributed Sampling is very similar to Modified Monte Carlo simulation. The primary difference is that Distributed Sampling begins simulation when the remaining samples at a particular node is less than three times the branches from that node. At this point, the remaining samples are distributed using the Modified Monte Carlo technique. Basically, Distributed Sampling is the Modified Monte Carlo technique, distributing fractions of samples down the branches until a small number remain. Then the

simulation continues using the Modified Monte Carlo technique. This method of simulation is recommended for models with decisions near the beginning of the tree.

Appendix I: Technology Data Set and Explanation

The technologies used for this analysis were selected for remediation of the INEL Test Pit 9. The waste in Pit 9 consists mainly of transuranic waste in drums, boxes, and other containers. The measurements for this site were provided by INEL, with estimates from MSE. These values are shown below:

Surface Area	435,000 ft^2
Waste Volume	500,000 ft^3
Waste Mass (100 lb/ ft^2)	50,000,000 lb.
Containment Area	481,800 ft^2
Work Rate	8 hr. / day
(excluding Treatment)	240 days / year
Work Rate	24 hr. / day
(Treatment)	300 days / year

The data above was used to calculate and convert cost and time data for the technologies used in this analysis. The technology options for each process are listed below.

Characterization:
1) Rapid Geophysical Surveyor
2) VETEM
3) High resolution Imaging Using Holographic Impulse Radar Array

Stabilization:
1) In Situ Cementation
2) Innovative Grouting and Retrieval
3) In Situ Vitrification

Retrieval:	1) Retrieval Demonstration	
	2) Remote Excavation System	
	3) Cooperative Telerobotic Retrieval System	
Treatment:	1) Cementation	
	2) Plasma Centrifugal Furnace	
	3) Stratex	
Disposal:	1) Yucca Mountain Disposal(Off-Site)	
	2) On-Site Disposal	
Containment:	1) Monolithic Confinement	
	2) In Situ Encapsulation of Buried Waste	
	3) Soil Saw (Horizontal)	
Monitoring:	1) Yucca Mountain Disposal (Off-Site)	
	2) On-Site Disposal	

The following spreadsheets contain the data for the technologies considered in this analysis. The first spreadsheet contains the actual data that was supplied by MSE. In the second spreadsheet, these values are converted to common units for cost and time using the measurements and site characteristics given above. Calculations were used for technologies that did not give worst case, best case, or average values. Typical percentages for cost and time overruns as well as best case percentages were used to calculate values not provided. The percentages used for these calculations are given below. These values are estimates taken from a DOE Project Performance Study which

investigated the cost and schedule performance of DOE environmental remediation projects [DOE: 1993, 111].

Cost			Time		
Best Case	Average	Worst Case	Best Case	Average	Worst Case
94%	100%	148%	77.5%	100%	142%

The data shown in the following spreadsheet is one of three types. Some of the values were taken directly from literature or from the principle investigators for the specific technologies. Other data values were calculated from the above percentages, while the remaining data values were estimates from MSE. All data values should be considered notional and should not be used to determine funding or project status.

For the first spreadsheet, values in italics are MSE estimates. The values in bold are from DOE literature or principal investigator surveys. The values for In-Situ Cementation O&M elements, and for the Retrieval Demo O&M elements were taken from the "Remediation Technologies Screening Matrix Reference Guide" [EPA/542/B-94/013, 1994]. The values for Cementation and On-Site Disposal were taken from previous research [White et al., 1995]. All other bold values were taken from the survey results of technology principal investigators for MSE.

	R&D Cost			R&D Time			O&M Cost			O&M Time			Diposal Factor	P(use)
	worst	avg	best	worst	avg	best	worst	avg	best	worst	avg	best		
Characterization														
Rapid Geoph. Surveyor		0			0		500$/hr	250$/hr	100$/hr	143 hr	71.5 hr	35.25 hr		100
VETEM		235000		4	2	1	1000$/hr	500$/hr	200$/hr	143 hr	71.5 hr	35.25 hr		90
High Res Imag.		2M		5	3	2	1000$/hr	500$/hr	200$/hr	143 hr	71.5 hr	35.25 hr		90
Stabilization														
In Situ Cementation		0			0		194$/T		111$/T	40 T/hr		80 T/hr		95
Innov. Grouting & Ret	600000	450000	300000	8	6	4		15M$/acre		2	1	0.75		95
In Situ Vitr.	6M	5M	4M	4	2	1.5	1$/lb	0.4$/lb	0.15$/lb	1T/hr	3T/hr	4T/hr		50
Containment														
Monolith. Confine.		0			0		20$/sq ft	10$/sq ft	5$/sq ft	2	0.75	0.5		80
In Situ Encap.	8.6M	4.3M		8	6	4	4$/sq ft		3$/sq ft	2	1	0.75		90
Soil Saw (Horiz)	6M	5M	3M	6	5	3	40$/sq ft	30$/sq ft	25$/sq ft	1	0.75	0.5		100
Retrieval														
Retrieval Demo		0			0			50$/T			10000T/mo			100
Remote Excav. Sys	350K	130K	0	1	0.5	0	180$/T	90$/T	60$/T		6600T/mo			95
Coop. Tele. Ret.	20M	10M	8M	5	3	2.5	5000$/T	2000$/T	1000$/T	0.5 cu ft/min	1 cu ft/min	2 cu ft/min		90
Treatment														
Cementation		0			0			50$/T			20000 T/mo		2	85
Plasma Furnace		11M		3	2	1	6$/lb	2.5$/lb	1$/lb	500 lb/hr	1000 lb/hr	2200 lb/hr	0.4	90
STRATEX		350K		6	3	1.5		200$/cu yd			5000$/lb		0.4	95
Disposal														
Yucca Mtn Off-Site		0		50	15	12	6300$/cu m	6000$/cu m	5100$/cu m		0			99
On-Site		0			0		300$/cu m	285$/cu m	270$/cu m		0			95
Monitoring														
Yucca Mtn Off-Site		0		50	15	12		0			0			100
On-Site		0			0			1.84$/cu m/yr			0			100

		R&D Cost			R&D Time			O&M Cost			O&M Time			Diposal Factor	P(use)
		worst	avg	best	worst	avg	best	worst	avg	best	worst	avg	best		
Characterization															
	Rapid Geoph. Surveyor		$0			0		$41,625	$20,812	$8,325	0.07448	0.03724	0.01835		100
	VETEM	$347,800	$235,000	$220,900	4	2	1	$83,250	$41,625	$16,650	0.07448	0.03724	0.01835		90
	High Res Imag.	$2,960,000	$2,000,000	$1,880,000	5	3	2	$83,250	$41,625	$16,650	0.07448	0.03724	0.01835		90
Stabilization															
	In Situ Cementation		$0			0		$48,500,000	$30,055,560	$27,750,000	0.32552	0.21954	0.16276		95
	Innov. Grouting & Ret	$600,000	$450,000	$300,000	8	6	4	$22,200,000	$15,000,000	$14,100,000	2	1	0.75		95
	In Situ Vitr.	$6,000,000	$5,000,000	$4,000,000	4	2	1.5	$50,000,000	$20,000,000	$7,500,000	4.34028	1.44676	1.08507		50
Containment															
	Monolith. Confine.		$0			0		$9,636,000	$4,818,000	$2,409,000	2	0.75	0.5		80
	In Situ Encap.	$8,600,000	$4,300,000	$4,042,000	8	6	4	$1,927,200	$1,498,900	$1,445,400	2	1	0.75		90
	Soil Saw (Horiz)	$6,000,000	$5,000,000	$3,000,000	6	5	3	$19,272,000	$14,454,000	$12,045,000	1	0.75	0.5		100
Retrieval															
	Retrieval Demo		$0			0		$1,850,000	$1,250,000	$1,175,000	0.29583	0.20833	0.16146		100
	Remote Excav. Sys	$350,000	$130,000	$0	1	0.5	0	$4,500,000	$2,250,000	$1,500,000	0.44823	0.31566	0.24464		95
	Coop. Tele. Ret.	$20,000,000	$10,000,000	$8,000,000	5	3	2.5	$125,000,000	$50,000,000	$25,000,000	2.89352	1.44676	0.72338		90
Treatment															
	Cementation		$0			0		$1,850,000	$1,250,000	$1,175,000	0.14792	0.10416	0.08072	2	85
	Plasma Furnace	$16,280,000	$11,000,000	$10,340,000	3	2	1	$300,000,000	$125,000,000	$50,000,000	13.88889	6.94444	3.15657	0.4	90
	STRATEX	$518,000	$350,000	$329,000	6	3	1.5	$5,491,500	$3,703,700	$3,481,400	1.97222	1.38889	1.07639	0.4	95
Disposal															
	Yucca Mtn Off-Site		$0		50	15	12	$88,200,000	$84,000,000	$71,400,000		0			99
	On-Site		$0			0		$4,200,000	$3,990,000	$3,780,000		0			95
Monitoring															
	Yucca Mtn Off-Site		$0		50	15	12		0			0			100
	On-Site		$0			0		$721,675	$487,618	$458,361		0			100

1) **Data values in this type are taken from published sources or from technology principle investigators.**

2) Data values in this type are calculated values extrapolated using the percentages above.

3) *Data values in this type are estimates provided by MSE.*

Appendix J: Utility Function Calculations

The following information was used to develop the utility functions for cost and time. These functions were developed for strategies with and without stabilization.

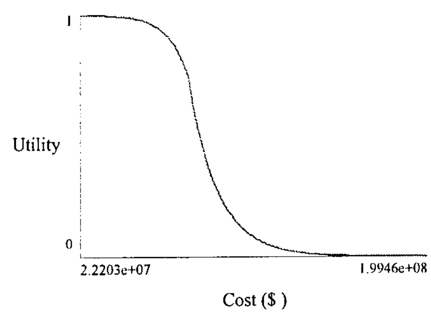
	Worst Cost	Best Cost	Worst Time	Best Time
With Stabilization	$199,464,000	$22,202,800	30.52 yrs	1.68 yrs
Without Stabilization	$214,427,000	$6,563,650	30.20 yrs	0.80 yrs

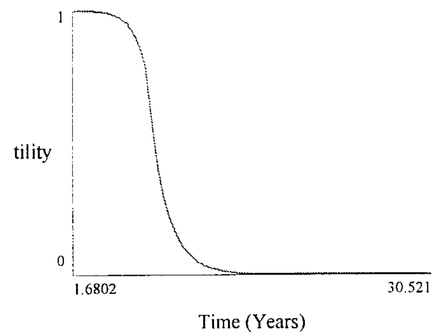
	Target Cost	Target+10%	Target+25%
With Stabilization	$70,000,000	$77,000,000	$87,500,000
Without Stabilization	$60,000,000	$66,000,000	$75,000,000

	Target Time	Target+10%	Target+25%
With Stabilization	7 yrs	7.7 yrs	8.75 yrs
Without Stabilization	6 yrs	6.6 yrs	7.5 yrs

The following functions were used as the attribute utility functions for strategies with and without stabilization. The graphs are shown followed by the formulas used to create them. The utility functions for strategies with stabilization are given with the utility functions for strategies without stabilization on the following pages:

With Stabilization





If cost $<$ 77,000,000:

$$U(cost) = 1.001 - 0.0001273e^{(0.00000009852 \bullet cost)}$$

Else:

$$U(cost) = -0.000002347 + 121e^{(-0.00000006601 \bullet cost)}$$

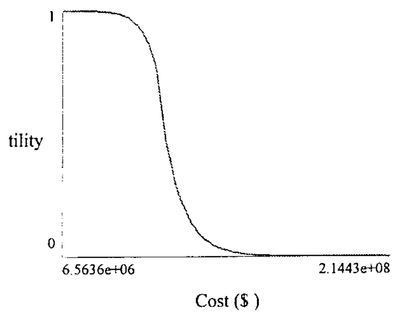
If time $<$ 7.7:

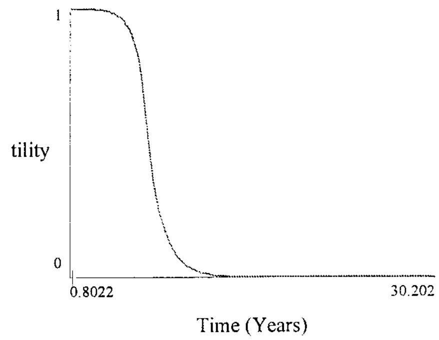
$$U(time) = 1 - 0.0001245e^{(0.9879 \bullet time)}$$

Else:

$$U(time) = -0.000000000002095 + 121e^{(-0.6601 \bullet time)}$$

Without Stabilization





If cost < $66,000,000:

$$U(cost) = 1 - 0.0001234e^{(0.0000001154 \bullet cost)}$$

Else:

$$U(cost) = -0.00000000958 + 121e^{(-0.00000007702 \bullet cost)}$$

If time < 6.6:

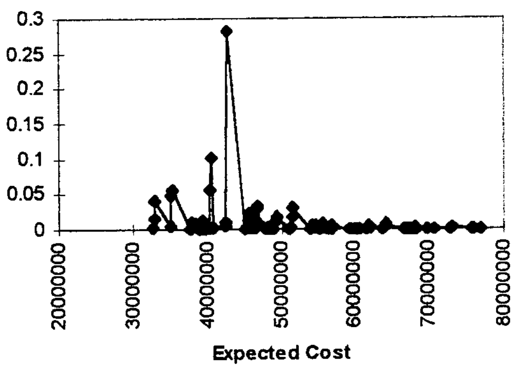
$$U(time) = 1 - 0.0001238e^{(1.153 \bullet time)}$$

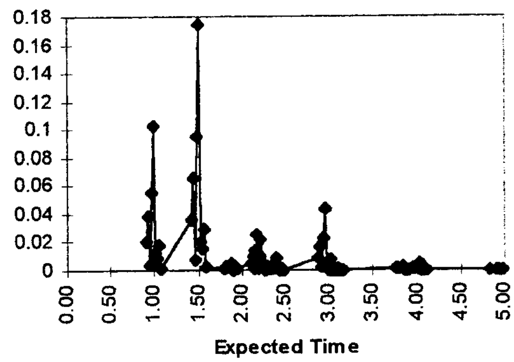
Else:

$$U(time) = -0.0000000000000001066 + 121e^{(-0.7702 \bullet time)}$$

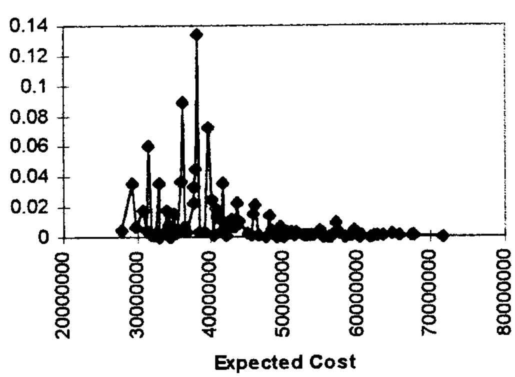
Appendix K: Cost and Time Frequency Distributions for Scenario 1

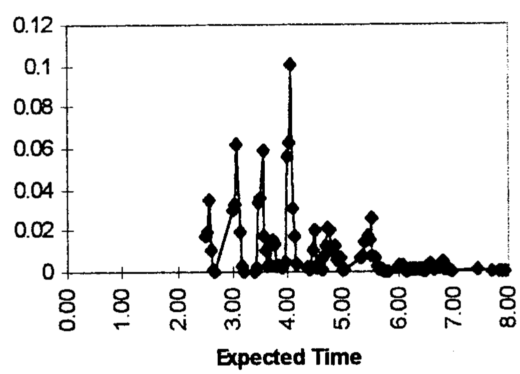
The following graphs are the frequency distributions of cost and time for the top five remediation strategies in Scenario 1. The graphs are shown with the strategy listed beneath each set of distributions.



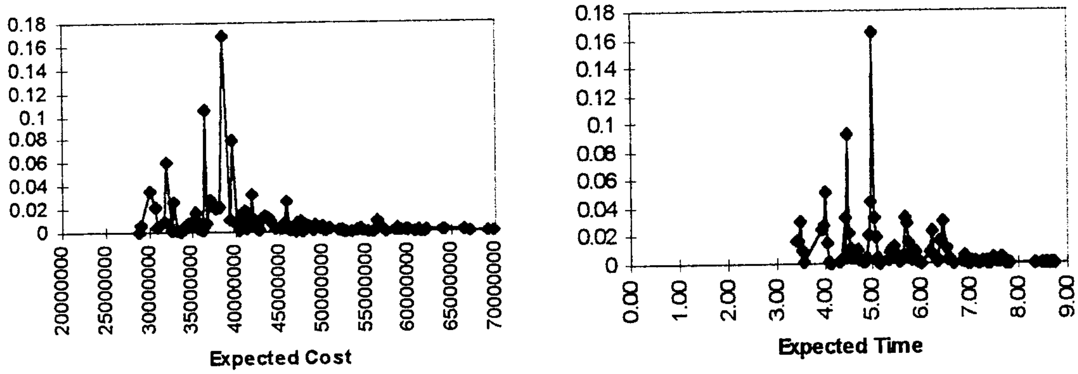


(CA-1, S-1, C-1, M-2)

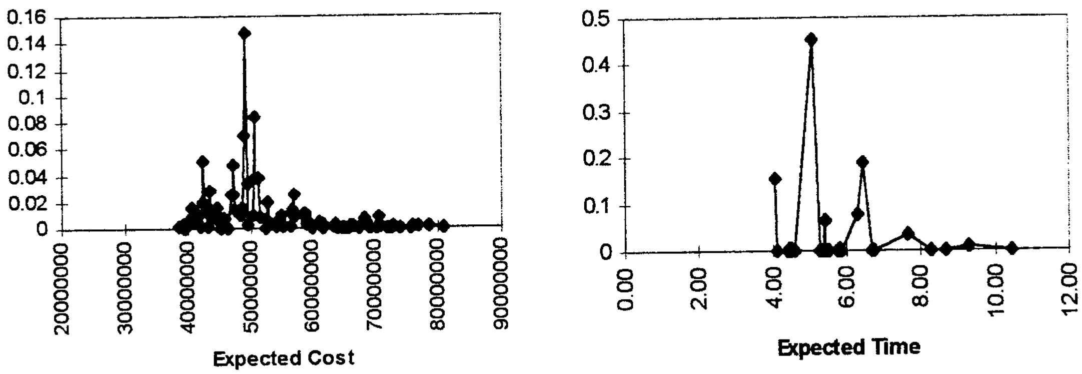




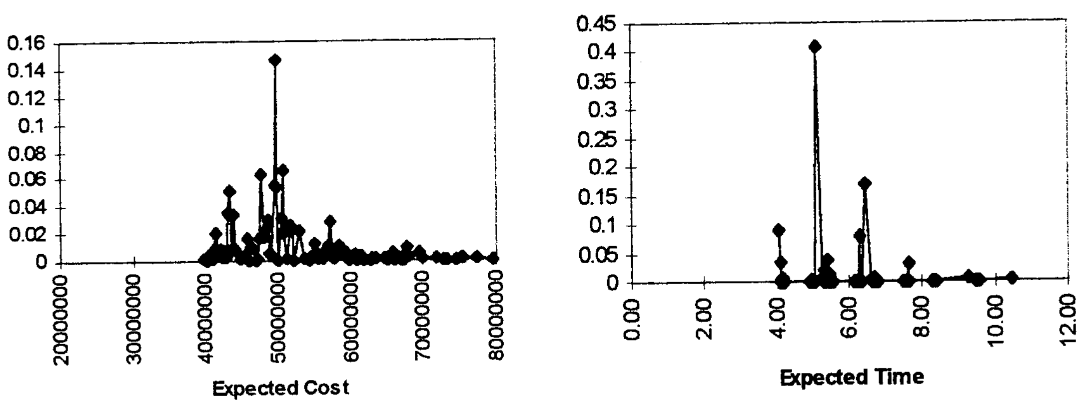
(CA-2, S-1, C-1, M-2)



(CA-3, S-1, C-1, M-2)



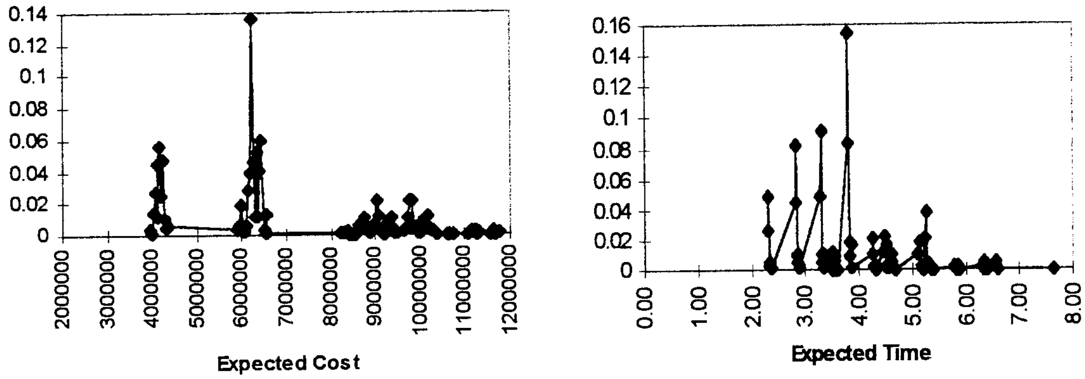
(CA-2, S-1, C-3, M-2)



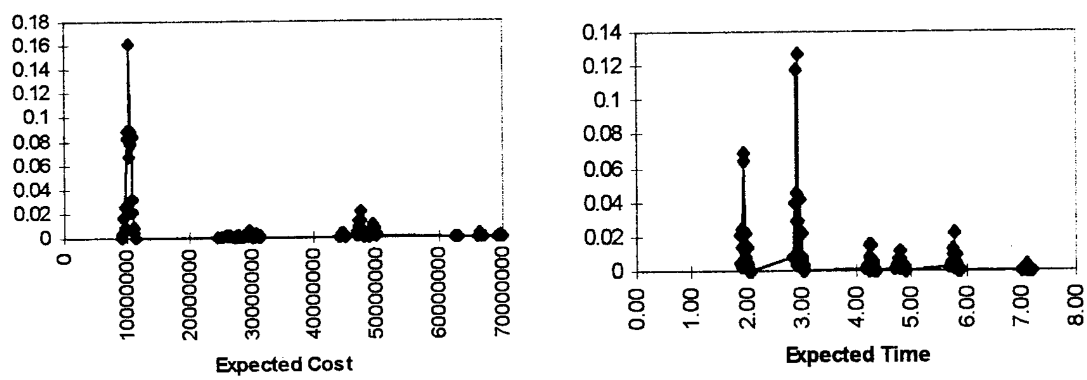
(CA-3, S-1, C-3, M-2)

Appendix L: Cost and Time Frequency Distributions for Scenario 2

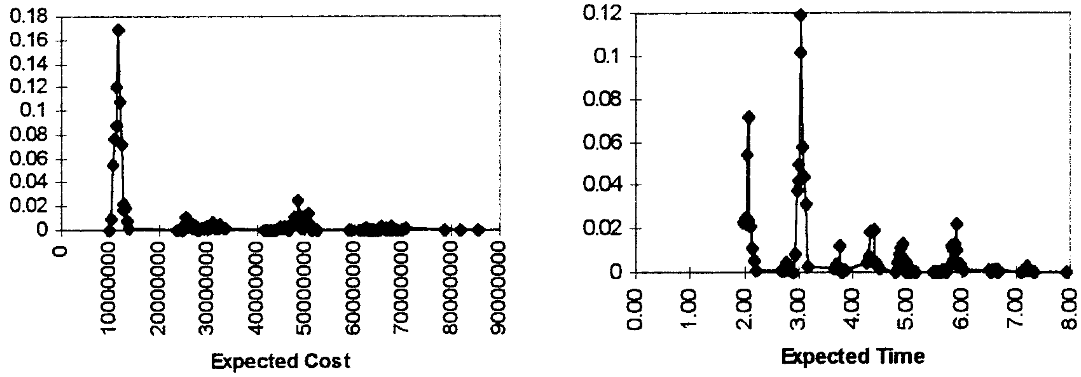
The following distributions are the frequency of cost and time for the different characterization technologies. The graphs are shown with the strategy below each set of distributions.



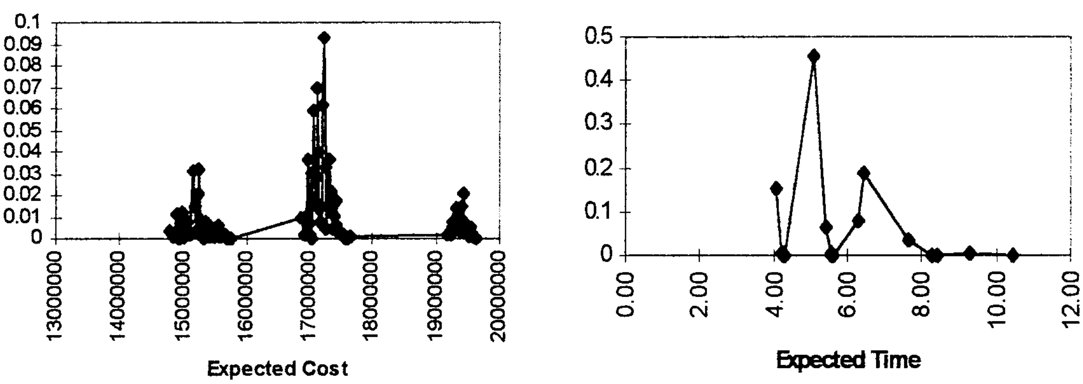
(CA-2, C-1, M-2)



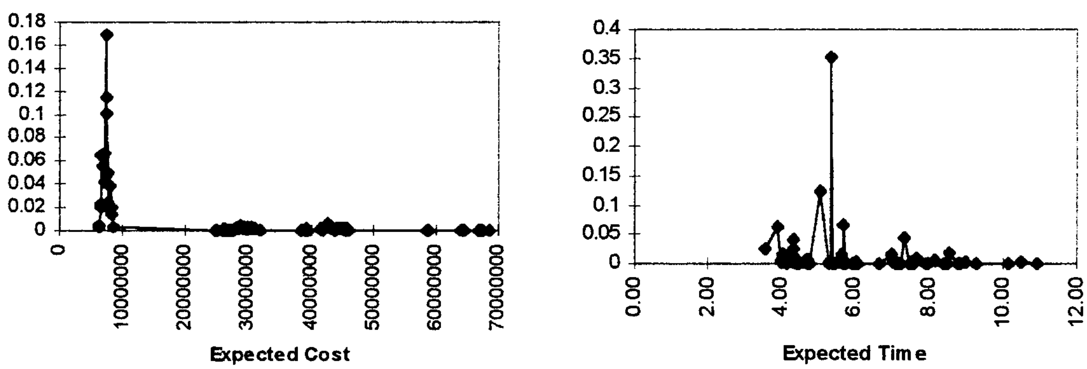
(CA-2, R-1, T-1, D-2, M-2)



(CA-2, R-2, T-1, D-2, M-2)



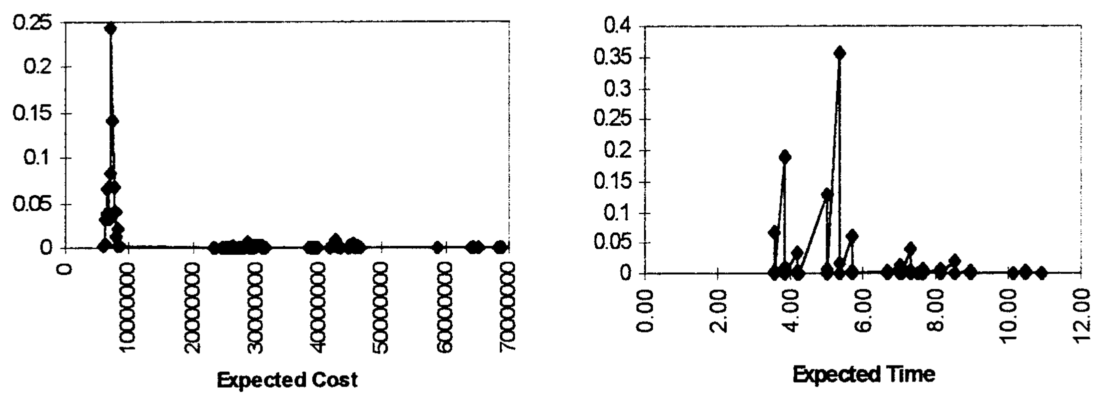
(CA-2, C-3, M-2)



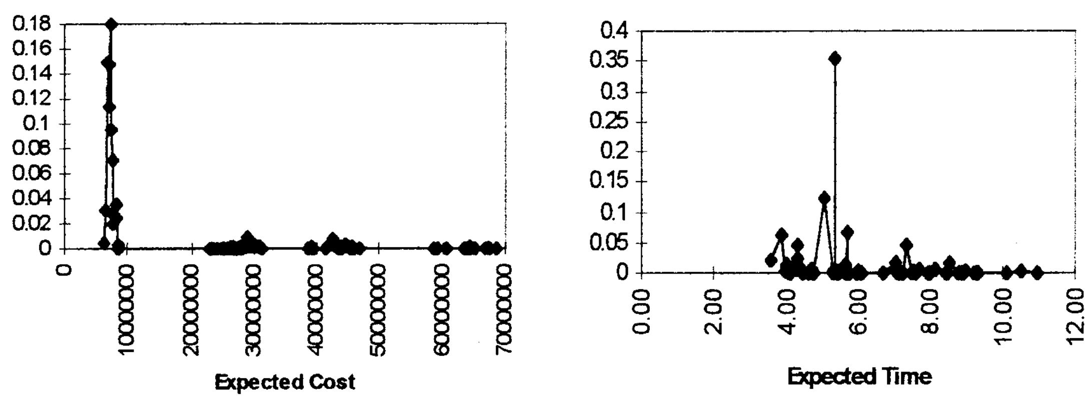
(CA-2, R-1. T-3, D-2, M-2)

Appendix M: Cost and Time Frequency Distributions for Scenario 3

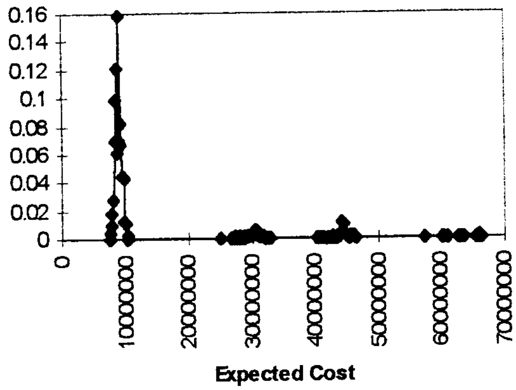
The following distributions are the frequency of cost and time for the strategies in Scenario 3. The graphs are shown with the strategy listed below each set of distributions.

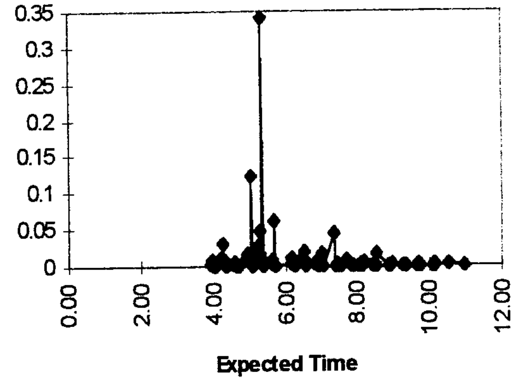


(CA-1, R-1, T-3, D-2, M-2)



(CA-2, R-1, T-3, D-2, M-2)





(CA-3, R-1, T-3, D-2, M-2)

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